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Influence of Car Park Proximity on Air Pollutant Concentrations at a Level 5 Hospital Outpatient Ward

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Abstract

Air quality is a critical factor in maintaining health and well-being, influencing both current conditions and future outcomes. Hospitals are one of the sensitive areas of our society, for they are built as sanctuaries for treatment and recovery, making the quality of paramount importance. This study investigates the impact of traffic-related emissions on indoor air quality within a Level 5 Hospital outpatient ward. Measurements were taken over five consecutive days, revealing that while CO_2 levels generally remained within safe limits, there were instances where concentrations exceeded 3000 ppm, categorizing them as "Hazardous." Notably, particulate matter ($PM_{2.5}$ and PM_{10}) levels fluctuated significantly, with peak concentrations observed during working hours correlating with increased vehicle activity. The data indicated that $PM_{2.5}$ levels reached as high as 75 $\mu g/m^3$, with 91.68% of recorded values exceeding the World Health Organization's (WHO) and Environmental Protection Agency 24-hour mean threshold of 25 $\mu g/m^3$. Similarly, PM10 concentrations peaked at 120 $\mu g/m^3$, with 61.19% of values surpassing the WHO threshold of 50 $\mu g/m^3$, both of which pose serious health risks, particularly to vulnerable populations such as pregnant women, infants, and the elderly. Additionally, the study highlighted the critical role of wind direction in pollutant dispersion, with specific patterns contributing to elevated indoor concentrations. These findings underscore the urgent need for targeted interventions and proactive air quality management strategies in healthcare facilities, including the strategic design of hospital wards away from primary emission sources and the promotion of electric vehicle use to mitigate traffic-related emissions.

Keywords

Air Quality, Hospital Wards, Vehicle Emissions, Particulate Matter, Wind Direction, Scalar dispersion, Carpark and Driveway

1. Introduction

Generally, poor air quality is the world's single largest environmental health risk. Specifically, the transport sector is responsible for a large proportion of air pollution, as well as being a leading source of greenhouse gas (GHG) emissions and an estimated 4.2 million premature deaths attributed to ambient (outdoor) air pollution (World Health Organization-Transport-Health Risks-Air Pollution 2024). Vehicle emissions carry various pollutants, namely particulate matter, oxides of carbon, oxides of nitrogen, oxides of Sulphur and unburnt hydrocarbons [1]. Extensive research has been carried out to analyze the effects and correlation between vehicle emissions and the negative health impacts on a broader scale under multiple case studies (WHO), road traffic congestion and pollution levels in canyons and intersections in the CBDs and highways [2] [3]. However, there are limited studies on the dispersion of vehicle emissions within healthcare facilities.

Several pilot studies of indoor air quality in residences and office buildings show that pollutant concentrations are always higher indoors than outdoors as a result of accumulation and poor air life (air exchange rate) [4]. Air pollution within indoor environments, particularly hospital wards, represents a critical yet often overlooked dimension of public health. The health impacts of airborne particulate matter (PM) are well-documented, with increased inhalation exposure correlating strongly with adverse health outcomes and understanding the dynamics of PM and oxides of Carbon exposure indoors, especially in sensitive environments such as hospitals [5]. Elevated exposure to airborne particulate matter is a significant concern due to its association with various negative health effects. PM_{10}, $PM_{2.5}$, unburnt hydrocarbons and CO can be inhaled deeply into the lungs, where it may contribute to chronic respiratory conditions, cardiovascular diseases, and exacerbation of existing health problems, especially for the most vulnerable group of patients (children, expecting women and the elderly) [6] [7]. The health risks associated with these emissions are influenced by various factors, including the size, composition, and concentration of particles in the air. Accurate assessment and effective control of PM_{10}, $PM_{2.5}$ and CO exposure necessitate a thorough understanding of how they are emitted, transported, and inhaled in indoor settings.

Particulate matter (PM) from vehicle emissions, particularly from exhausts and road dust, includes PM_{10} and $PM_{2.5}$ generally. PM_{10}, with particles ≤10 micrometers in diameter, can penetrate the upper respiratory tract, while $PM_{2.5}$, with particles ≤2.5 micrometers, can reach deeper into the lungs and enter the bloodstream [7] [8]. In hospital wards, high PM concentrations can exacerbate respiratory conditions in patients, impair lung function, and contribute to cardiovascular issues. CO (Carbon Monoxide) is a colorless, odorless gas produced by incomplete combustion of fossil fuels [9]. Elevated CO levels can lead to reduced oxygen transport in the blood, causing headaches, dizziness, and impaired cognitive function and in hospital settings, this can be particularly harmful to patients with cardiovascular or respiratory problems [6], whereas CO_2 (Carbon Dioxide), is a by-product of combustion, which accumulates in poorly ventilated areas. Elevated CO_2 levels can also cause discomfort, headaches, and impaired cognitive function and also can affect staff and patient well-being, potentially complicating the management of sensitive health conditions [10].

Indoor air quality is influenced by multiple factors, including building design, ventilation rates, room size, effectiveness of ventilation systems, airflow patterns, and the rate of air exchange, which play crucial roles in determining the concentration and distribution of PM within indoor spaces. Additionally, human-related factors such as occupancy, activity levels, and individual inhalation rates contribute to exposure variability [11]. For most primary pollutants, that is, those emitted directly from sources (rather than formed, for example, by chemical reactions in the atmosphere), concentrations, exposures, and doses are proportional to emissions. That is, if all other variables are fixed, then doubling the rate of emissions leads to a doubling of the inhalation dose rate, for cases where the receptor is directly facing the emission source (Ward facing car park and drive way) the indoor pollutant concentration levels are averagely proportional to the pollutant mass released [12].

A study in 401 Military General Hospital of Athens touches slightly on the issue but focuses on the general carbon footprint of transport activities within the facility [13]. A study by K. Hill and F. Qiao (2016) addresses the vehicle traffic in the drive way and emissions released that compromise the air quality of fast-food restaurant [14]. The study is consistent with this study concerning traffic jams near fast food or closer to the hospital ward. This poses challenges of incomplete fuel combustion, resulting in toxins that compromise the air quality of the nearby building. [14] This highlighted the effect of the pollutant source (vehicle emission) proximity to the receptor (fast food restaurant). Less distance between the two locations results in concentrated exposure levels, which are coherently applicable to the carpark and drive way closeness to the outpatient ward at the hospital. Emissions released from a close distance reach the ward at the most high concentration for there is less temporal advantage for dilution, hence the patients experience an elevated pollutant exposure. A study by S. Sukoriansky, N. Dikovskaya, and B. Galperin [15] reported the behavior and transport mechanisms of the pollutant at the point of release and noted that they undergo two commonly known phenomena: Scalar dispersion and turbulent diffusion. Scalar dispersion, in the context of vehicle emissions, refers to the spread and dispersion of various vehicle emission constituents released into the atmosphere [16]. Vehicle emissions, primarily consist of exhaust gasses from automobiles, trucks, and other forms of fuel-based road transportation and dispersion of these emissions depends on traffic patterns, road conditions, and meteorological conditions. These factors can affect how pollutants disperse in the atmosphere, potentially leading to the formation of localized pollution hotspots or causing pollutants to be carried over long distances, impacting areas even far from the emission source [17]. Turbulent diffusion of vehicle emissions refers to the random and chaotic distribution of vehicle emissions in the atmosphere as a result of wind velocity fluctuations and pressure differences ultimately transporting the emissions largely by advection [18]. This paper delves into the intricate relationships between close (carpark and driveway) outdoor air pollution sources (vehicles) and the resulting emission concentration levels reaching the ward, influencing the impact of inhalation intake fractions on health within hospital wards. Understanding the inhalation intake fraction also has significant implications for health risk assessments and exposure control strategies. Inhalation intake fraction (ITF) is a crucial metric for evaluating indoor air pollution by measuring the ratio of the pollutant mass inhaled to the pollutant mass emitted from a source [19]. This metric integrates various factors affecting exposure, such as building characteristics, and pollutant attributes and accurate ITF values can help in predicting exposure levels based on emission rates and provide a basis for comparing different pollution scenarios [19].

2. Materials and Methods

Figure 1 presents a structured framework for the research project, divided into three distinct phases: Pre-Data Collection, Data Collection, and Post-Data Collection. Each phase consists of specific activities integral to the study. Pre-data collection (Phase One) involves preparatory tasks, primarily focused on obtaining ethical and institutional approvals, such as authorization letters from the university, Ministry of Health, and hospital ethical board approval. Another key aspect of this phase was site selection, involving a site survey of appropriate wardroom

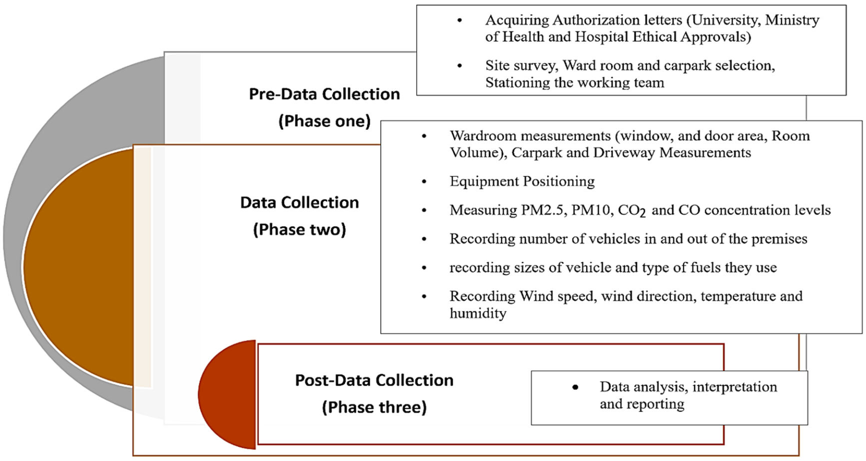
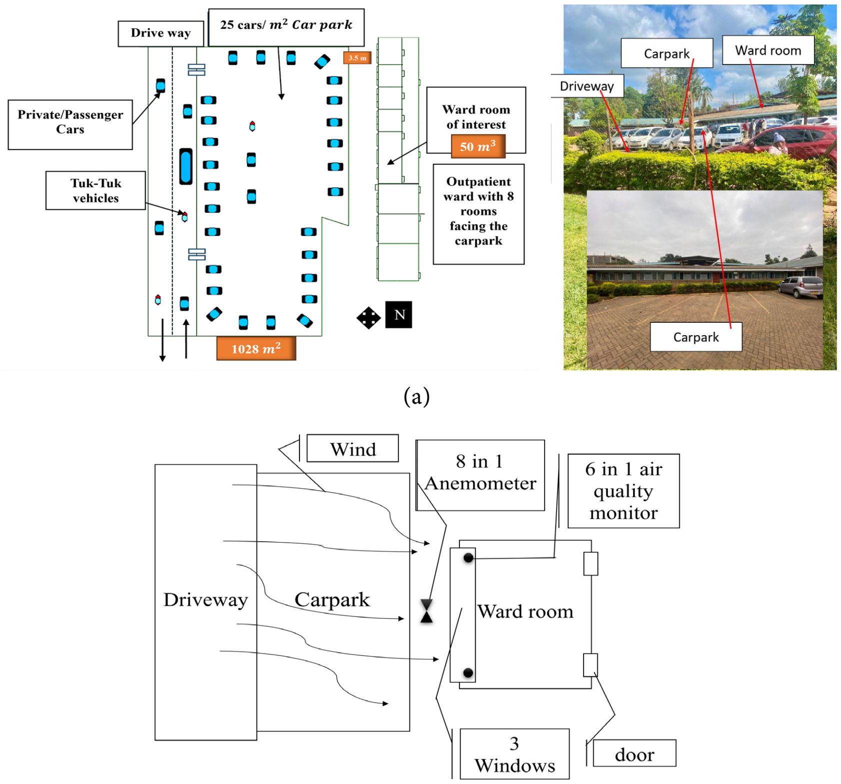


Figure 1. Methodological procedure (Pre-Data collection, data collection and post-data collection).

and car park for data collection. Data collection (Phase Two) is the core phase, focusing on conducting actual measurements and observations. During this phase, detailed wardroom measurements were taken, including window and door dimensions and overall room volume. Equipment was strategically positioned to ensure accurate collection of pollutant concentrations, including $PM_{2.5}$, PM_{10}, CO and CO_2. Simultaneously, vehicle data such as the number of vehicles entering and exiting the premises, vehicle size, and fuel type were recorded on a daily basis. Additionally, meteorological data, including wind speed, wind direction, temperature, and humidity, were captured as they are known to influence pollutant dispersion. Post-Data collection (Phase Three) focused on the analysis of the collected data involving data processing, interpretation of the results, and report generation based on the findings using MATLAB, Data tab and Origin softwares for statistical presentations.

Given the emission source as vehicles from the carpark and drive way, and the receptor being the adjacent ward (see **Figure 2(a)** and **Figure 2(b)**), the study investigated the pollutant mass reaching the ward associated with episodic outdoor to indoor emissions. By measuring PM_{10}, $PM_{2.5}$, CO, and CO_2 levels reaching the wardroom, the study aimed to explore the correlation between indoor concentration levels and emission location, spatiotemporal variability, and pollutant



(a)

(b)

Figure 2. (a): A lay out of the driveway and vehicle car park at the proximity of the hospital outpatient ward at the Level 5 Hospital; (b): A lay out of the driveway and vehicle car park at the proximity of the hospital outpatient ward room at the Level 5 Hospital.

transport mechanisms [16]. The findings from this study are expected to contribute to more precise exposure assessments, better-informed health risk evaluations, and improved strategies for managing indoor air quality and positioning healthcare wards.

2.1. Study Area

Although there are activities that stir up dust or release pollutants, such as vigorous exercise, which can significantly impact airborne particulate levels in the breathing zone [20] [21], this study did not account for these factors. Instead, it focused on analyzing the relationship between exterior to interior pollutant mass. Busy areas such as the hospital driveways and carparks give way to constant fluctuations of air quality within the ward rooms during working hours, induced by closeness of an area source adjacent to the ward (see **Figure 2(b)**). As seen in **Figure 2(a)**, the frequency of vehicles in and out of the car park, back and forth along the driveway could give rise to particulate matter ($PM_{2.5}$ and PM_{10}) from the wearing out of the road and tires, and oxides of carbon (CO and CO_2) from the vehicle exhaust emissions [22]. In both ways, the ward could be adversely affected, especially when the wind blows in the direction of the ward from the car park. After a pre-experiment investigation, four air quality monitors were employed interchangeably to measure the concentration levels of the main pollutants of interest namely $PM_{2.5}$, PM_{10}, CO and CO_2.

2.2. Materials

The 6 in 1 low-cost Air Quality Monitor (Model number: ACDqitifenxiyi394 and SKU: GE840IP19E2X2NAFAZ) was used to measure the concentration of PM2.5, PM_{10}, CO and $CO_{2.}$ The 8 in 1 Digital Anemometer (Model number: N/A and SKU: GE840IP3FZUDTNAFAMZ) by TARVIT was used to measure meteorological parameters of wind speed, wind chill, air temperature, humidity, heat index, dew point, barometric pressure and altitude. **Table 1** below, shows the detailed specification of the air quality monitor and the anemometer. Uncertainty in the measurements was estimated using Eq.1. Uncertainty analysis establishes the reliability of the results by quantifying measurement variability and identifying potential errors as it provides context to the data, enhancing instrument calibration, and facilitating outlier detection, ensuring robust conclusions [23]. This analysis strengthens comparability and reproducibility, guiding improvements in experimental design and supporting accurate risk assessments and informed decision-making [24].

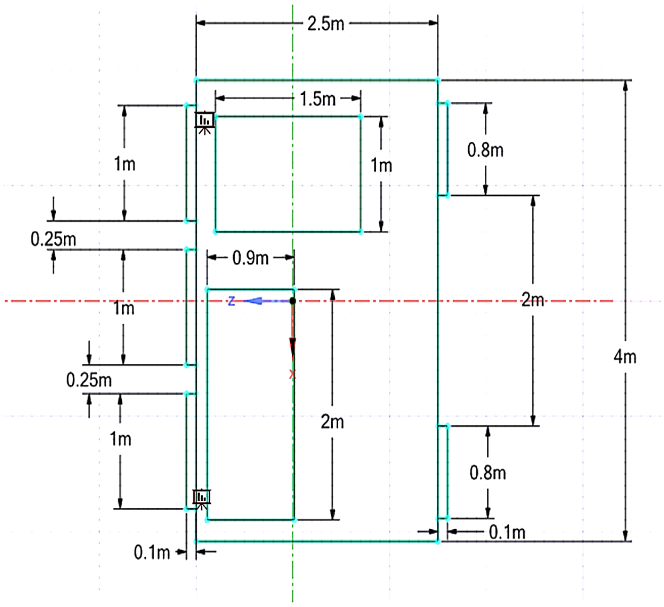
$$u(x)=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2} \tag{1}$$

where $u(x)$ is the standard uncertainty, n is the number of samples, x_i refers to each individual measurement and $\bar{x}$ is the mean value.

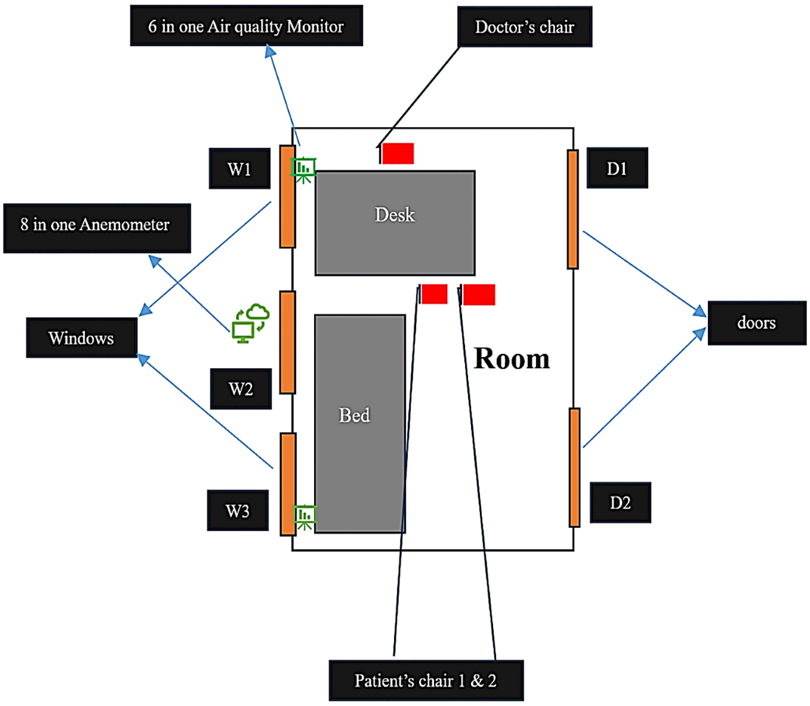
Table 1. Equipment details and accuracy: description of device name, measuring range, accuracy, and resolution.

No.	Device	Measuring Range	Accuracy	resolution
1	6 in 1 Air Quality Monitor, USB Charging Air Quality Meter, CO and CO_2 Detector, $PM_{2.5}$/PM_{10} Meter, TVOC, and HCHO Pollution Tester (Black)-Brand-Preshwous	1. CO [0 - 999] ppm 2. CO_2 [400 - 5000] ppm 3. PM10 [0 - 999] 1ug/m³ 4. PM2.5 [0 - 999] 1ug/m³	±10% (50 ppm ± 5%) ±10% ±10%	1 ppm 1 ppm 1 ug/m³ 1 ug/m³
2	Anemometer 8 in 1 Digital Anemometer Wind Speed, Wind Chill, Temperature Humidity, Heat Index, Dew Point, Barometric Pressure, Altitude Meter Brand-TARVIT Item-Weight-800 Grams Manufacturer-TARVIT	1. Wind speed [0 - 30] m/s 2. Temperature [−29 - 170]˚C 3. Humidity [0 - 100] % 4. Barometric Pressure [0 - 1100] hPa	±5% ±1 ±2% ±1.5	0.1 0.1 0.1 0.1

The experiment was carried out in the wardroom of interest as shown in Figure 2(a) of dimensions (4 m × 2.5 m × 5 m) to measure concentration levels of pollutants reaching the building. Figure 3(a) and Figure 3(b) show the location of the air quality monitors near the windows, positioned 3.4 m apart at window level breathing height (to avoid single device placement and recording bias) and as an endpoint to give average concentration results [25]. The 8 in 1 anemometer was placed outside the wardroom in between the carpark and the room to record temperature, wind speed and humidity as these influence advection and scalar dispersion of pollutants. The devices have an inbuilt time lag calibration system that takes about 5 minutes to acclimatize with the surrounding before use. Multiple monitors were employed so as to reduce bias by calculating the average value over each time interval as the final reading. Meteorological data of wind speed was validated using the Kenya-Nairobi-Thika weather forecast in which the values deviated by a margin of ±2% from each other.



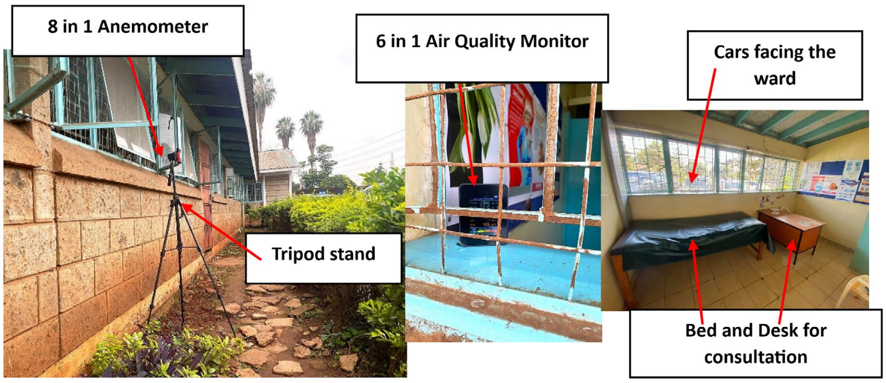
(a)



(b)

Figure 3. Hospital ward room dimensions and layout description.

For ethical considerations data was collected from outside the room, near the window, without any direct contact and engagement with the patients (see Figure 4), given that the building considered in the study is an outpatient ward (see Figure 5) where expecting women, children below 1 year of age and the elderly are attended. Monitoring protocol involved data collection from 0800 hrs to 1600 hrs (opening and closure of the outpatient ward facility respectively) East Africa Time (UTC/GMT+3), aiming to capture pollutant variations and their potential impact on occupants during that period. Data from all devices was manually collected at 5-minute intervals over a period of 5 consecutive days. Due to constraints in time, resources and procedures, the study was limited to a single location



(a) (b) (c)

Figure 4. Show Exterior-Interior ward room setup, equipment used and device positioning.

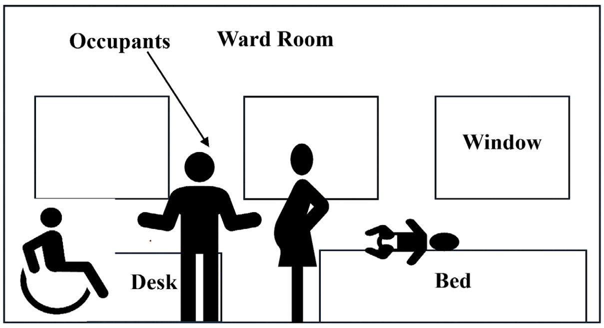


Figure 5. Patient categories served in the level 5 hospital outpatient ward in the study.

and a short monitoring period, rather than covering multiple hospital facilities or different seasons. This limitation allows use of single facility as a model for the future study. $PM_{2.5}$, PM_{10}, CO and CO_2 were recorded as outputs (dependent variables) and temperature, time, wind speed, wind direction, humidity and day time cloud cover were recorded as inputs (independent variables).

2.3. Equations

The data obtained from this study is frequently utilized in ITF applications to quantify the extent of emitted pollutants inhaled by individuals, providing valuable insights for exposure risk assessments.

$$ITF = \frac{I}{E} \tag{2}$$

where ITF stands for Inhalation Intake Fraction, I for mass of the pollutant inhaled by an individual (in micrograms) and E for mass of the pollutant emitted from the source (in micrograms) [5] [19]. To successfully calculate ITF, we consider both independent variables such as the concentration of each pollutant measured, mass emission rates (E) provided as the mass flow rate of pollutant and then the dependent variable inhaled mass (I) which is calculated based on the individual's tidal volume, exposure time, and pollutant concentration (children, pregnant women and the elderly have different breathing rates). Benefits of this approach is that ITF provides a way to assess how much pollutant from emissions reaches the vulnerable population and Health Risk Assessment allows quantification of health risks associated with exposure to these pollutants, informing mitigation strategies [26]. Consequently, the same data can be used with the Relative Risk (RR) where the coefficient values of the CRF (Concentration-Response Functions) are typically derived based on an Equation, which describes the risk of an adverse health effect among the population exposed to a higher ambient air pollution level relative to a lower ambient level.

$$RR = exp\left(\beta \times \Delta C\right) \tag{3}$$

Previous epidemiological studies by Am. J. Respir. Crit. Care Med. (1996), Azhdarpoor, A (2016) and Nawahda, A (2013) postulated that RR associated with ambient air pollution is in a linear relationship with the concentration level, with several alternative linear function models established as below, where c represents the concentration of air pollutants and c_t represents the minimum level below which there is no obvious adverse health impact (also called threshold value):

$$\begin{aligned}&\text{For } c < c_t,\ RR\ Lin50(c) = 1,\\ &\text{For } c_t < c < 50,\ RR\ Lin50(c) = 1 + \gamma(c - c_t),\\ &\text{For } c > 50,\ RR\ Lin50(c) = 1 + \gamma(50 - c_t).\end{aligned} \tag{4}$$

However, the studies focused on estimating the RR functions which are mainly carried out in Europe and North America, where the pollutant concentration is low. The models mentioned above may not be suitable for developing countries where the concentration of the pollutants is relatively higher, instead, use of the gradual diminution of the marginal increase in RR can be extracted from the logarithm model or power model of RR and concentration as discussed by J. O. Olawepo *et al.* (Mar. 2019), D. Olsson (2012) and M. Pascal *et al.* (Apr. 2013). Then WHO subsequently recommended the logarithmic model to measure the health impact attributable to air pollution at the national level by Paciorek (2012).

- Logarithm model:

$$\begin{aligned}&\text{For } c < c_t,\ RR\ Log(c) = 1,\\ &\text{For } c \ge c_t,\ RR\ Log(c) = [c + 1/c_t + 1]\rho.\end{aligned} \tag{5}$$

- Power model:

$$\begin{aligned}&\text{For } c < c_t,\ RR\ Power(c) = 1,\\ &\text{For } c \ge c_t,\ RR\ Power(c) = 1 + \theta(c - c_t)\eta\end{aligned} \tag{6}$$

Based on the above mathematical forms used for burden assessment, recent studies have also conducted the meta-analysis of observed data and proposed an integrated exposure-response function (IERs) that flattens out at high exposures:

$$\begin{aligned}&\text{For } c < c_t,\ RR\ IER(c) = 1,\\ &\text{For } c \ge c_t,\ RR\ IER(c) = 1 + \alpha\left[1 - exp\left(-\gamma(c - c_t)\delta\right)\right]\end{aligned} \tag{7}$$

where α, γ, and δ jointly characterize the CRF which is derived from a fitting process.

3. Results and Discussion

Level 5 Hospitals experience significant traffic due to their standardized service provisions, making them relatively busy areas [27]. **Tables 2(a)-(c)** below illustrates the vehicle movement at the hospital's main gate through three visualizations: The "Vehicle In/Out" **Table 2(a)** shows the percentage of vehicles entering and exiting the hospital premises in a given duration of 0800 hrs to 1600 hrs. **Table 2(b)** provides a breakdown of the number of vehicles based on the type of fuel they use, Petrol, Diesel, or Electric, with petrol vehicles being the most common while **Table 2(c)** shows the distribution of vehicle types visiting the hospital daily, with "SMALL" vehicles (private passenger car vehicles) comprising the majority, followed by three-wheelers (commonly known as "TUKTUK") and then "LARGE" vehicles (commercial vehicles).

Table 2. (a): Vehicle entrance and exit data for Level 5 Hospital; (b): Frequency vs fuel type; (c): Daily percentages of vehicle sizes within the premises.

(a)

Day	Vehicle IN (%)	Vehicle OUT (%)
Day 1	62	38
Day 2	62.7	37.3
Day 3	62.3	37.7
Day 4	54	46
Day 5	65.1	34.9

(b)

Day	FUEL (Petrol - P), (Diesel - D) & (Electric - E)	Frequency
Day 1	P	245
	D	49
	E	6
Day 2	P	237
	D	125
Day 3	P	226
	D	137
Day 4	P	220
	D	102
Day 5	P	243
	D	130

(c)

Day	Vehicle size Large - L, Small - S, Tuk-Tuk - T	%
Day 1	L	8.67
	S	70.7
	T	20.7
Day 2	L	43.1
	S	56.9
Day 3	L	41.3
	S	58.7
Day 4	L	34.8
	S	65.2
Day 5	L	29.5
	S	70.5

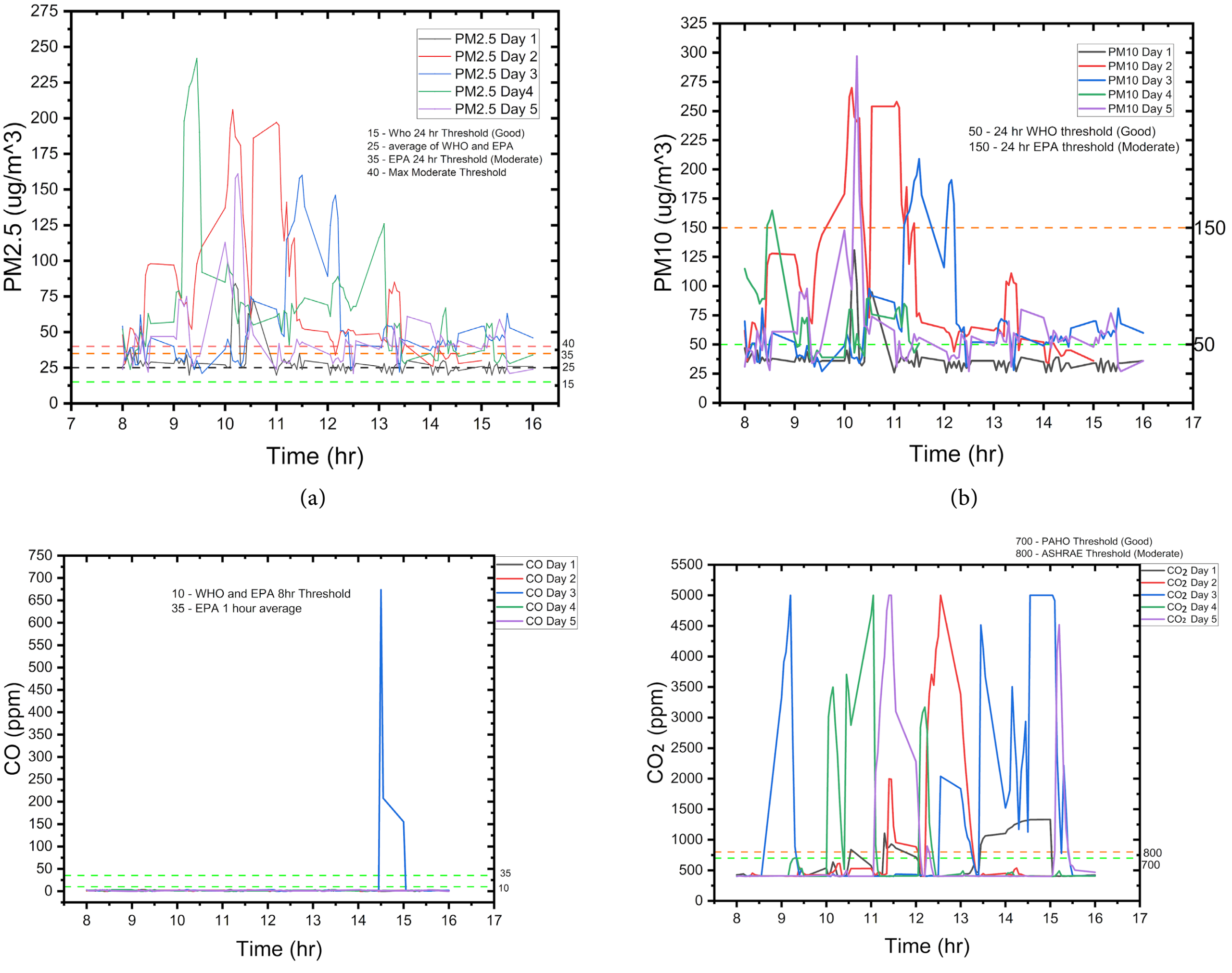
A higher percentage of vehicles are entering the premises compared to those exiting shown as "IN" (entering), while "OUT" (exiting) suggesting a steady influx of vehicles through hospital entrance, potentially leading to congestion or increased exposure to vehicular emissions. The imbalance between vehicles entering and exiting also imply a buildup of vehicles during certain periods, which might have implications for traffic management and pollution control strategies. In all the cases a significant 68.1% of vehicles were petrol-powered, followed by diesel-powered vehicles 31.6% and only a small fraction is electric at 0.349%. The overwhelming dominance of petrol and diesel vehicles indicated a higher potential for emissions of pollutants like CO, CO_2, NOx, and $PM_{2.5}$, PM_{10}.

This could have serious implications for air quality, especially in high-traffic environments such as hospitals. Additionally, the low number of electric vehicles suggests a limited adoption of cleaner technologies, highlighting the need for policies promoting electric vehicles or other low-emission alternatives to mitigate environmental and health impacts in Africa as a whole. **Table 2(c)** presents the types of vehicles categorized as "Small" (private vehicles) "Tuktuk type", and "Large" vehicles (trucks and buses). Small vehicles dominated with 64.2%, 3.61% as Tuktuk, and as 32.2% as Large. The prevalence of small vehicles suggests a potentially lower total emission load compared to a scenario with more large vehicles, however, this depends on the specific emission profiles of each vehicle type. The "Tuktuk" category (3.61%) represents a significant proportion, which have unique emission characteristics, especially the older models with less efficient engines seen within the premises. Large vehicles (32.2%), although constituting a smaller proportion, are likely to have higher individual emissions, which could significantly contribute to localized air pollution.

3.1. Emission Daily Trends

There were consistent morning peaks in $PM_{2.5}$ and PM_{10} concentrations across all days as depicted in **Figure 6** above correlating with higher traffic activity and stagnant air conditions. The CO_2 levels exhibit significant and frequent threshold violations, with many readings reaching 5000 ppm, indicating localized emission build-ups. The $PM_{2.5}$ and PM_{10} values exceeded WHO and EPA standards of 15 $\mu g/m^3$ and 35 $\mu g/m^3$ (average threshold of 25 $\mu g/m^3$) [28] [29], respectively, with 91.68% of $PM_{2.5}$ readings and 61.19% of PM_{10} readings surpassing the average safe limit threshold. There is a notable divergence between CO and CO_2 concentrations, with CO generally within recommended limits, whereas CO_2 shows extreme variability. The CO concentrations show fluctuating spikes throughout the day, reaching a maximum of 3 ppm. Despite these variations, the values largely remain within health-recommended standards, with only 0.64% exceeding the acceptable threshold of 10 ppm [30].

For CO_2, 75.27% of the recorded values stayed within the recommended health limit of 800 ppm [31] [32] while 24.73% surpassed this threshold. The morning peaks in $PM_{2.5}$ and PM_{10} suggest that cooler morning air traps pollutants near



(a) (b)

(c) (d)

Figure 6. Daily emission trends vs concentrations over time (Working Hours).

the ground due to the urban boundary layer effect, limiting their dispersion until the atmosphere becomes more turbulent later in the day [33] [34]. The significant CO_2 readings point to environmental factors like reduced atmospheric mixing or local geometrical features that trap pollutants, especially near areas like the driveway and car park. The contrast in CO and CO_2 behavior emphasizes that CO_2 is more influenced by environmental trapping mechanisms. The linear relationship between $PM_{2.5}$ and PM_{10} **Figure 7** emissions indicated a consistent source of pollution, though deviations at higher concentrations suggest specific events or sources causing abnormal increases in PM_{10}. The high frequency of $PM_{2.5}$ and PM_{10} threshold violations reflects serious health concerns, particularly for vulnerable groups like children, the elderly, and expecting women who frequently visit healthcare facilities. The spatial proximity of emission sources and their impact on pollutant hotspots emphasize the need for targeted mitigation strategies. Addressing air quality in urban healthcare settings requires comprehensive measures, such as dynamic traffic management, the installation of green barriers, and improved ventilation systems [35]. The findings underscore the importance of considering environmental design and human behavior in developing effective air quality management strategies. **Figure 7** below showcases the linear relationship between $PM_{2.5}$ and PM_{10}, further supporting the significance of emission concentration hotspots and highlighting the impact of facility layout on air quality.

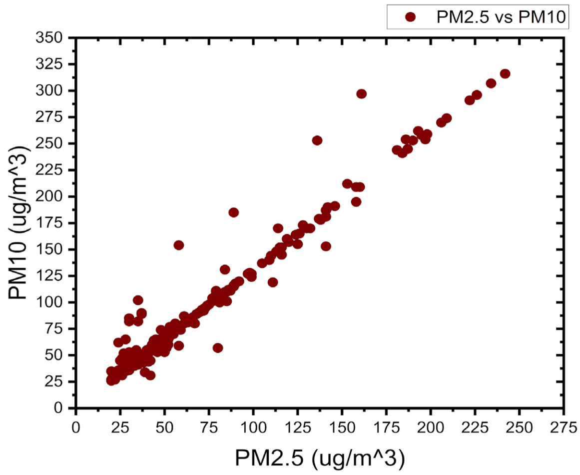
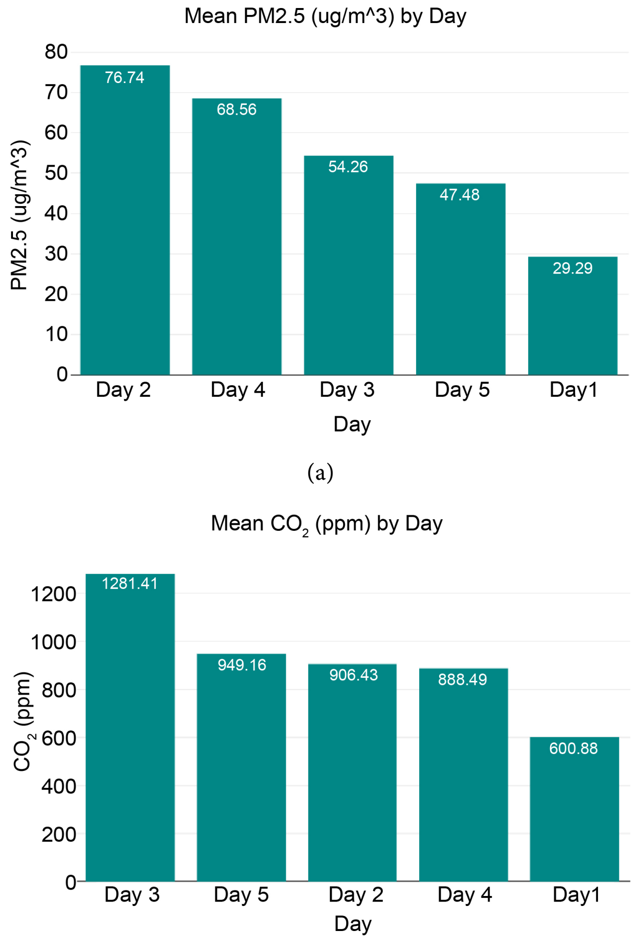


Figure 7. Relationship between both Particulate Matters (PM_{10} and $PM_{2.5}$).

3.2. Emission vs Day

Figure 8 presents a comparison of the daily mean concentrations of various air pollutants across a five-day period, ordered by activity level for each day (see the supporting document for additional data). The analysis reveals that the mean concentration of $PM_{2.5}$ peaked on Day 2 at 76.74 μg/m^3, while the lowest value was recorded on Day 1 at 29.30 μg/m^3. Similarly, PM_{10} concentrations followed the same pattern, with the highest level observed on Day 2 at 102.76 μg/m^3 and the lowest on Day 1 at 38.74 μg/m^3. In terms of gaseous pollutants, CO levels exhibited a significant spike on Day 3, reaching 12.23 ppm, whereas other days showed much lower and relatively consistent values, ranging from 1.35 to 1.53 ppm. CO_2 concentrations also showed a distinct pattern, with the highest mean value recorded on Day 3 at 1281.41 ppm and the lowest on Day 1 at 600.88 ppm.

The data in **Figure 8** and **Table 3** highlights several key observations, notably, Day 2 recorded the highest concentrations of particulate matter ($PM_{2.5}$ and PM_{10}), suggesting an increase in dust and fine particles. This spike is likely attributable to external activities or increased traffic, particularly associated with the closure of the Medical Training College (MTC) on the western side of the area (see **Figure 2(a)**), which may have disturbed particulate matter from the driveways or parking areas. On Day 3, there was a pronounced spike also in CO and elevated CO_2 levels, indicating a strong link to localized vehicle emissions, such as idling cars during patient drop-offs or traffic congestion near the hospital ward.



(a)

(b)

Figure 8. Daily pollutant means (Descending order).

Table 3. Daily mean values for each pollutant and overall, five days mean value for each.

Day	$PM_{2.5}$ (ug/m^3) (approx.)	PM_{10} (ug/m^3) (approx.)	CO (ppm) (approx.)	CO_2 (ppm) (approx.)
1	29.30	38.74	1.53	600.88
2	76.74	102.76	1.35	906.43
3	54.26	70.64	12.23	1281.41
4	68.56	92.31	1.51	888.49
5	47.48	62.76	1.50	949.16
5 day overall	**55.27**	**73.44**	**3.62**	**925.27**

The simultaneous increase in CO and CO_2 concentrations reinforce the idea that vehicle activity, rather than dust or other environmental factors alone, was a significant contributor to air pollution on this day. The consistently lower pollutant concentrations recorded on Day 1 suggest reduced traffic or fewer scheduled activities, emphasizing the impact of operational schedules on air quality. These findings imply that the timing and nature of activities within the facility can directly shape pollution patterns. The variability in pollutant levels observed throughout the study period (**Table 3**) underscores the need for adaptive air quality management strategies. Potential measures could include scheduling high-traffic events during low-emission periods, enhancing ventilation during peak hours, or implementing traffic management systems to mitigate pollution. Such strategies would be essential for minimizing exposure to harmful pollutants and protecting the health of individuals within the hospital environment.

3.3. Emission means vs Wind Direction

Figure 9 illustrates the mean concentration of pollutant $PM_{2.5}$ categorized by wind direction, with additional data on PM_{10}, CO, and CO_2 available in the supporting document. The results show that the highest mean $PM_{2.5}$ concentration, 98.56 μg/m^3, is associated with the ENE (East-Northeast) wind direction, followed closely by INNE (Inner Northeast) at 96.2 μg/m^3, while the lowest mean concentration of 26.18 μg/m^3 occurs with wind from the N (North). For PM10, the highest mean concentration is linked to NNE (North-Northeast) at 135.2 μg/m^3, followed by ENE at 118.24 μg/m^3, with the lowest concentration of 34.42 μg/m^3 from the N. The mean CO concentration is highest at 10.34 ppm with winds from the E (East) and lowest at 0.85 ppm with WNW (West-Northwest) winds. CO_2 levels are highest at 1247.91 ppm when the wind comes from the E, followed closely by ENE at 1260.4 ppm, with the lowest concentration of 536.45 ppm recorded when the wind comes from the WNW.

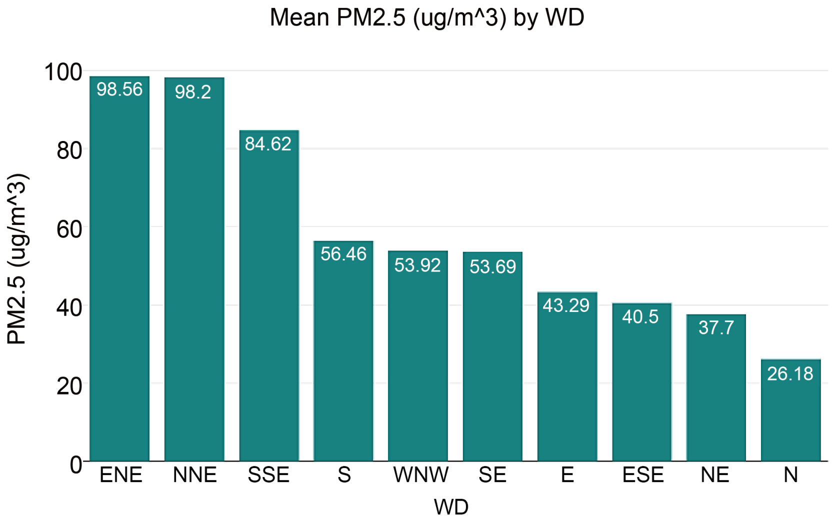


Figure 9. Pollutant means vs. wind direction: Analysis of $PM_{2.5}$ vs. wind direction.

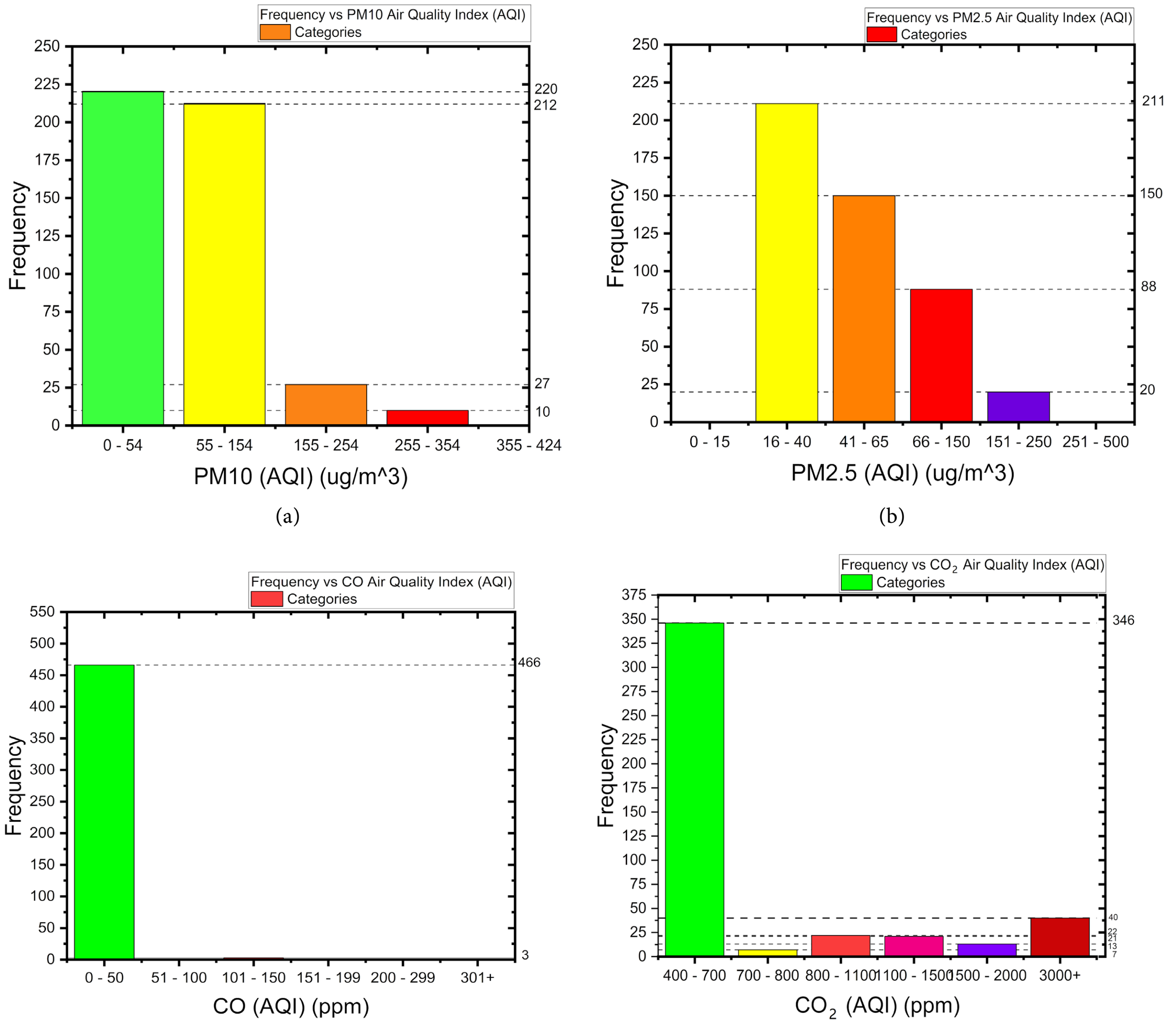
The key observations from this data include a clear pattern where wind from certain directions especially NNE, ENE, and SSE (see **Figure 2(a)**) were associated with higher particulate matter concentrations. The CO levels generally remained stable and low, under 2 ppm, except for a notable spike to 10.34 ppm, which was linked to a nearby vehicle idling for about 10 minutes. CO_2 concentrations peaked when winds originated from the east and east-northeast, with elevated levels also recorded from the southeast, while the lowest concentrations were seen with winds from the west-northwest. These observations suggest that wind direction plays a critical role in the transport and dispersion of pollutants. The higher particulate matter concentrations with ENE and NNE winds may indicate pollutant transport from emission sources located in those directions, exacerbated by simultaneous meteorological factors and traffic activity. The unusual spike in CO concentration, unrelated to wind, highlights how localized sources, such as idling vehicles, can significantly influence pollutant levels. CO$_2$ concentrations were affected by scalar dispersion, where low wind speeds limit advection, making dispersion the primary mechanism for pollutant distribution. This explains the elevated concentrations observed in directions such as southeast and south-southeast. The results imply that wind direction, in conjunction with the layout of the area including the driveway, traffic patterns, and building orientation, significantly impacts pollutant dispersal and air quality [36]. The frequent occurrence of ENE winds and their alignment with high traffic activity areas underscore the need for strategic air quality management measures. Understanding these patterns can inform interventions like optimizing building orientation, managing traffic flow, or enhancing ventilation to mitigate pollution exposure.

3.4. Emission Frequency vs Air Quality Index

The Air Quality Index (AQI) is a scale that indicates the current levels of air pollution and provides forecasts of expected pollution levels. **Figure 10** shows a relationship between frequency and air quality index, and the frequency of recorded pollutant values refers to how often a pollutant concentration is measured and falls within a specific range. This frequency distribution can be analyzed over time to determine how often the air quality is within certain AQI categories (e.g., Good, Moderate, Unhealthy), as shown in the table below the chart [37]-[39]. The colors displayed in the charts correspond to the air quality index representation colors demonstrating the air quality conditions. **Table 4** shows Air Quality Index numbers and their categories.

Table 4. Air Quality Index numbers, categories, and concentration cut points for PM$_{2.5}$, PM$_{10}$, CO, and CO$_2$ [39].

AQI Category	AQI Color	PM2.5	PM10	CO	CO$_2$
Good	Green	0 - 15	0 - 54	0 - 50	400 - 700
Moderate	Yellow	16 - 40	55 - 154	51 - 100	701 -- 800
Unhealthy for sensitive groups	Orange	41 - 65	155 - 254	101 - 150	801 - 1100
Unhealthy	Red	66 - 150	255 - 354	151 - 199	1101 - 1500
Very Unhealthy	Purple	151 - 250	355 - 424	200 - 299	1501 - 2000
Hazardous	Maroon	251 - 500	425 - 604	301+	3000+



(a)

(b)

(c)

(d)

Figure 10. Relationship between Frequency (F) and Air Quality Index (AQI).

The charts illustrate the frequency and AQI ranges for $PM_{2.5}$, with $PM_{2.5}$ chart observations falling within the "Moderate" category (16 - 40 μg/m^3) with a frequency of 211, followed by "Unhealthy for Sensitive Groups" (41 - 65 μg/m^3) at 150 occurrences but with fewer occurrences of "Unhealthy in general" (66 - 150 μg/m^3) and "Very Unhealthy" (151 - 250 μg/m^3) levels, with only 68 and 20 observations, respectively. For PM_{10}, most data points fall under the "Moderate" (55 - 154 μg/m^3) and "Unhealthy for Sensitive Groups" (155 - 254 μg/m^3) categories, with frequencies of 210 and 213. Higher levels of PM_{10}, categorized as "Unhealthy" (255 - 354 μg/m^3) and "Very Unhealthy" (355 - 424 μg/m^3), are much less frequent. This distribution indicates that the majority of the days were within acceptable ranges to moderate pollution levels, but there were notable instances when PM levels were high enough to pose health risks.

CO results show that nearly all observations fall within the "Good" range (0 - 50 ppm), with a frequency of 446, indicating minimal concern for CO pollution over the five-day period but chart for CO_2 indicates that most readings are in the "Good" (400 - 700 ppm) range with 344 occurrences, however, there are notable frequencies in higher ranges, "Moderate" (700 - 800 ppm) at 78 occurrences, "Unhealthy for Sensitive Groups" (1100 - 1500 ppm) with 21 occurrences, and "Very Unhealthy" (1500 - 2000 ppm) with only 40 occurrences. A small number of observations fall into the "Hazardous" category (3000+ ppm) at 1 occurrence. A notable observation from **Figure 10** is the correlation between peak pollutant levels and operational activity in the hospital area, particularly during working hours.

The patterns reveal that while overall air quality remains within acceptable ranges most of the time, the outliers and occasional spikes coincide with periods of increased traffic and patient drop-offs near the outpatient ward. This depicts that local emissions from vehicle activity at the driveway and nearby parking areas play a critical role in air quality fluctuations within the hospital premises. The contrast between $PM_{2.5}$ and CO_2 trends also highlight a dual pollution challenge: fine dust particles with localized health risks for sensitive groups and elevated CO_2 levels signaling poor ventilation and inefficient air circulation in certain areas. The presence of CO_2 levels in "Unhealthy for Sensitive Groups" and "Very Unhealthy" categories raises concerns about the adequacy of current mitigation strategies. This points to the potentially overlooked impact of vehicle idling and patient transport patterns on indoor air quality, reinforcing the need for sustainable traffic management policies within hospital environments. This insight emphasizes that air quality management in healthcare settings must not only address external pollutants but also focus on optimizing operational logistics and vehicle emission near sensitive zones [40]. Implementation of green infrastructure, traffic controls, and monitoring systems is crucial for ensuring sustainable health facilities, promoting patient wellness, and aligning with environmental best practices [35].

3.5. Uncertainty Analysis

This study provides scientific and practical insights into air quality by analyzing the mean concentrations, standard deviations, and standard uncertainties of $PM_{2.5}$, PM_{10}, CO, and CO_2. The $PM_{2.5}$ mean concentration of 54.74 $\mu g/m^3$ with a standard uncertainty of 1.80 $\mu g/m^3$ indicates that, despite a high standard deviation of 39.02 $\mu g/m^3$, the average concentration is reliable. This demonstrates the capability of the instrument to capture short-term pollution spikes from traffic surges and weather shifts, offering insights into transient pollution events and their effect on air quality. For PM_{10}, the mean concentration of 72.73 $\mu g/m^3$ and standard uncertainty of 2.43 $\mu g/m^3$ highlights greater variability (standard deviation of 52.52 $\mu g/m^3$) due to frequent dust and particle surges. However, the small standard uncertainty ensures that the mean concentration remains precise and this result demonstrates the robustness of the monitoring system under dynamic conditions, providing reliable data for policymaking and threshold exceedance reporting.

Table 5. Uncertainty analysis of each pollutant measurement.

Pollutant	No. of data points	Mean value ($\bar{x}$) (μg/m³)/(ppm)	Sum of Squared Differences $\sum(x_i - \bar{x})^2$	(σ)Standard deviation (μg/m³)/(ppm)	Standard uncertainty (μg/m³)/(ppm)	Accuracy
$PM_{2.5}$	469	54.74	712,647.30	39.02	1.80	±10%
PM_{10}	469	72.73	1,290,982.15	52.52	2.43	±10%
CO	469	3.68	516,516.74	33.22	1.53	±10%
CO_2	469	925.68	553,646,746.74	1087.66	50.22	50 ppm ± 5%

The CO analysis reveals a mean concentration of 3.68 ppm with a standard uncertainty of 1.53 ppm. While high variability (standard deviation of 33.22 ppm) is observed due to occasional extreme outliers (e.g., 674 ppm), the small standard uncertainty indicates that the central tendency of the data remains stable and this emphasizes the importance of outlier management to ensure data reliability and underscores the sensitivity of the instrument in capturing both regular and episodic pollution events [41]. Lastly, CO_2 has a mean concentration of 925.68 ppm and standard uncertainty of 50.22 ppm, with readings ranging from 400 ppm to 5000 ppm and the large variability (standard deviation of 1087.66 ppm) reflects periodic vehicle emissions. Despite this variability, the standard uncertainty aligns well with the accuracy of the instrument, showing that the system can accurately track dynamic CO_2 levels, critical for early detection of hazardous indoor environments. Overall, the analysis in **Table 5** highlights the importance of precision amidst variability, where the small standard uncertainties across pollutants show that mean concentrations remain meaningful despite fluctuations. Furthermore, outlier management ensures that extreme values do not skew results while preserving meaningful variability and the ability to detect pollution spikes episodic events demonstrates the instruments' effectiveness for real-time risk assessments and targeted interventions, providing critical data for informed decision-making [24].

4. Conclusion

This study underscores the significant influence of traffic-related emissions on indoor air quality in healthcare environments. The clear correlation between vehicle emissions from nearby car parks and driveways and the elevated levels of $PM_{2.5}$, PM_{10}, CO, and CO_2 within the outpatient ward highlights an urgent need for targeted interventions. Additionally, the findings demonstrate that wind direction plays a critical role in pollutant transport, with specific wind patterns contributing to elevated pollutant concentrations indoors. These results indicate a pressing health concern, particularly for vulnerable patient groups, who are most at risk from exposure to air pollutants. This study did not quantify specific health risks or track significant changes in patients' health over time due to poor air quality, primarily because of limited resources and time constraints. However, the observed pollutant concentrations during peak traffic hours suggest a substantial potential for adverse health outcomes as mentioned by Laumbach R in 2010 and Luke Curtis in 2006. Given these insights, it is imperative that healthcare facilities adopt proactive air quality management strategies. Key recommendations include the careful design and positioning of hospital wards away from primary emission sources, the implementation of mitigation measures to reduce traffic-related emissions (encouraging the use of electric vehicles and minimizing vehicle idling near hospital entrances), and the establishment of continuous air quality monitoring programs. These interventions are essential not only to improve indoor air quality but also to safeguard the health of both patients and healthcare workers.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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