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PM2.5 Air Pollution and Hospital Admissions: A Data-Driven Analysis of Outpatient and Inpatient Trends Across Age Groups

Kantapong Songkram[1], Punjarat Chaibunkaew[2], Maisoon Akhunsada[3], Kanyawee Teepun[4], Ashwin Upra[5], Pongkit Ekvitayavetchanukul[6]

Samakkhiwitthayakom school[1],

Pholwitaya school[2],

PNU wittayanusorn school[3],

Rayongwittayakom School[4],

Samakkhiwitthayakhom school[5],

The Board of Khon Kaen University Affairs, Khon Kaen University.[6]

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KEYWORDS

PM2.5, Air Pollution, Hospital Admissions, Healthcare Burden, Outpatient Visits, Inpatient Admissions, Age Group Vulnerability, Environmental Health.

ABSTRACT:

Air pollution, particularly fine particulate matter (PM2.5), has been increasingly linked to adverse health outcomes, leading to a surge in hospital admissions. This study presents a data-driven analysis of the relationship between PM2.5 levels and hospital admissions, focusing on both outpatient department (OPD) visits and inpatient department (IPD) admissions across different age groups. Through a systematic examination of hospital records over multiple weeks, we identify a strong correlation between elevated PM2.5 concentrations and increased hospital visits, particularly among elderly individuals (>60 years), who show the highest inpatient admissions. Our results reveal that when PM2.5 levels exceed 40 µg/cu.m, hospital visits peak, whereas a decline in pollution levels corresponds with a significant reduction in admissions. These findings emphasize the critical role of air quality management in public health and healthcare system preparedness. The study provides compelling evidence for policymakers, healthcare institutions, and environmental health researchers to implement targeted interventions aimed at mitigating the health burden associated with air pollution, particularly for vulnerable populations.

1. Introduction

1. Background and Significance

Air pollution is a major global health crisis, with particulate matter (PM2.5) posing severe risks to human health. PM2.5 (particles with a diameter of ≤2.5 µm) can penetrate deep into the respiratory system, leading to a range of cardiopulmonary diseases, respiratory infections, and other systemic complications (WHO, 2021). Numerous epidemiological studies have established a strong link between short-term exposure to elevated PM2.5 levels and increased hospital visits, particularly among vulnerable populations such as children, the elderly, and individuals with pre-existing conditions (Chen et al., 2020; Liu et al., 2022).

2. Research Problem and Gap

While previous studies have investigated the long-term health effects of PM2.5 exposure, there is limited research on its immediate impact on hospital admissions, especially in terms of outpatient department (OPD) visits versus inpatient department (IPD) admissions across different age groups. Understanding how fluctuations in air pollution levels influence both outpatient and inpatient hospital utilization is crucial for healthcare system preparedness and policy development.

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3. Research Objective

This study aims to provide a data-driven analysis of the relationship between PM2.5 levels and hospital admissions, specifically examining:

- The correlation between PM2.5 concentration and OPD/IPD trends.
- How different age groups (0-10, 11-20, 51-60, and >60 years) respond to air pollution exposure.
- The potential healthcare burden associated with rising PM2.5 levels.

4. Hypothesis and Research Questions

Based on prior findings, we hypothesize that higher PM2.5 levels will be associated with increased OPD and IPD cases, with elderly patients being the most affected. The study seeks to answer:

1. How do fluctuations in PM2.5 levels affect OPD visits and IPD admissions?
2. Which age groups experience the most significant increase in hospital visits due to air pollution?
3. What threshold levels of PM2.5 contribute to a notable surge in hospital admissions?

5. Study Relevance and Contribution

This research provides critical insights for public health officials, hospital administrators, and policymakers, enabling:

- Better forecasting of hospital admissions based on air pollution trends.
- Policy recommendations for air quality management and healthcare preparedness.
- Public awareness campaigns targeting high-risk groups.

By leveraging real-world hospital data, this study strengthens the understanding of PM2.5's direct impact on healthcare systems and underscores the urgency of pollution control measures to mitigate its effects.

2. Methodology

1. Study Design

This study employs a retrospective observational approach to analyze the relationship between PM2.5 levels and hospital admissions across different age groups. The research utilizes real-world hospital data collected over multiple weeks, focusing on trends in outpatient department (OPD) visits and inpatient department (IPD) admissions. A quantitative data analysis method is applied to assess the correlation between air pollution exposure and hospital visits.

2. Data Collection

2.1 Hospital Admission Data

- The dataset includes OPD and IPD records from the Medicine and Otolaryngology departments.
- Patient categories: Four age groups (0-10, 11-20, 51-60, >60 years).
- Time frame: Weekly hospital records from January to February 2025.
- Metrics:
  - OPD visits per age group
  - IPD admissions per age group
  - Department-wise analysis (Medicine & Otolaryngology)

2.2 Air Pollution Data

- PM2.5 concentration levels (µg/cu.m) were obtained for each corresponding week.
- The data was sourced from official environmental monitoring agencies or hospital-linked air quality monitoring systems.

3. Data Processing and Analysis

3.1 Statistical Analysis

To determine the relationship between PM2.5 levels and hospital admissions, the following analyses were conducted:

3.1.1 Descriptive Statistics:

- Weekly averages, standard deviations, and trends of OPD, IPD, and PM2.5 levels were computed.

3.1.2 Correlation Analysis:

- Pearson correlation coefficient (r) was used to measure the relationship between PM2.5 levels and hospital admissions (OPD & IPD).

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- Correlation strength was interpreted as:
  - 0.0 – 0.3: Weak correlation
  - 0.3 – 0.6: Moderate correlation
  - 0.6 – 1.0: Strong correlation

3.1.3 Regression Analysis:

- A linear regression model was applied to predict how changes in PM2.5 influence OPD/IPD admissions.

3.1.4 Age Group Comparison:

- A comparative analysis was conducted to identify which age group exhibited the highest response to air pollution levels.

4. Ethical Considerations

- Data Anonymity: Patient data was anonymized to maintain confidentiality and comply with ethical research standards.

- Environmental Data Compliance: PM2.5 readings were sourced from officially verified environmental monitoring stations.

5. Limitations of the Study

- Potential Confounding Factors: The study does not account for seasonal illnesses, temperature variations, or concurrent outbreaks.

- Short Study Period: Data is limited to a two-month observation period, which may not fully capture long-term trends.

- Limited Geographic Scope: Findings are based on hospital data from a specific location, limiting generalizability to broader populations.

3. Results and Discussion

1. Descriptive Analysis

1.1 PM2.5 Trends Over the Study Period

The PM2.5 levels fluctuated between 35 to 42 µg/cu.m during the study period (January - February 2025). The highest PM2.5 concentration was observed in mid-January (42 µg/cu.m), followed by a decrease in late January (37 µg/cu.m) and early February (35 µg/cu.m). However, a slight increase was noted in mid-February (39 µg/cu.m), before stabilizing.

1.2 Hospital Admissions Trends (OPD & IPD)

- OPD visits showed a moderate increase when PM2.5 levels rose, peaking during the highest pollution weeks.

- IPD admissions, particularly in the >60 years age group, exhibited a stronger increase in response to rising PM2.5 levels, suggesting more severe health effects in older patients.

- The lowest OPD and IPD figures were recorded when PM2.5 levels declined, reinforcing the potential impact of air pollution on hospital visits.

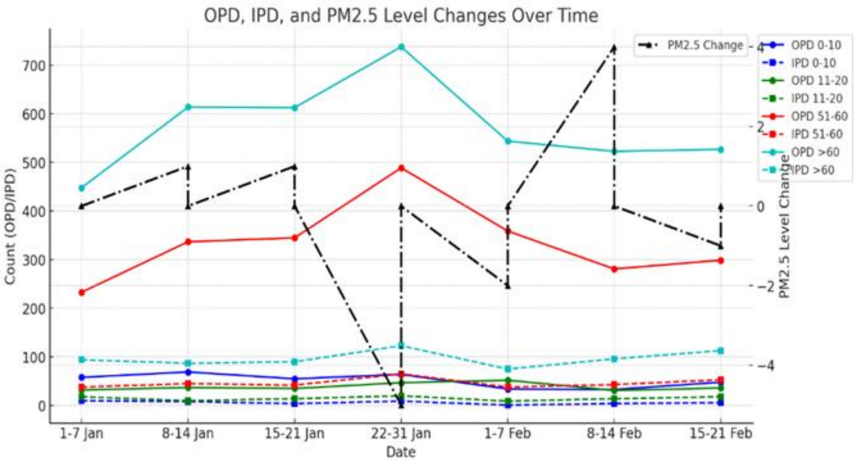

Figure1: weekly variations in air pollution (PM2.5)

Observations:

- Significant fluctuations in PM2.5 changes are noticeable, especially around late January.

- More than 60 age group consistently has the highest OPD and IPD counts.

- PM2.5 decreases in late January and early February, then fluctuates again in mid-February.

Table 1: Hospital Admissions and PM2.5 Air Pollution Levels Over Time

Date	Department	Age(year)	Outpatient dept.(person)	Inpatient dept.(person)	PM2.5 (µg/cu.m)
1-7 Jan 2025	Medicine Department	0-10	58	10	40
1-7 Jan 2025	Medicine Department	11-20	32	18	40
1-7 Jan 2025	Medicine Department	51-60	233	38	40
1-7 Jan 2025	Medicine Department	>60	448	94	40
1-7 Jan 2025	Otolaryngology	0-10	39	-	40
1-7 Jan 2025	Otolaryngology	11-20	15	-	40
1-7 Jan 2025	Otolaryngology	51-60	22	-	40
1-7 Jan 2025	Otolaryngology	>60	18	-	40
8-14 Jan 2025	Medicine Department	0-10	69	8	41
8-14 Jan 2025	Medicine Department	11-20	37	10	41
8-14 Jan 2025	Medicine Department	51-60	337	45	41
8-14 Jan 2025	Medicine Department	>60	614	87	41
8-14 Jan 2025	Otolaryngology	0-10	35	-	41
8-14 Jan 2025	Otolaryngology	11-20	11	-	41
8-14 Jan 2025	Otolaryngology	51-60	20	-	41
8-14 Jan 2025	Otolaryngology	>60	23	1	41
15-21 Jan 2025	Medicine Department	0-10	55	4	42
15-21 Jan 2025	Medicine Department	11-20	35	14	42
15-21 Jan 2025	Medicine Department	51-60	345	42	42
15-21 Jan 2025	Medicine Department	>60	613	90	42
15-21 Jan 2025	Otolaryngology	0-10	44	-	42
15-21 Jan 2025	Otolaryngology	11-20	9	-	42
15-21 Jan 2025	Otolaryngology	51-60	26	-	42
15-21 Jan 2025	Otolaryngology	>60	29	1	42
22-31 Jan 2025	Medicine Department	0-10	64	9	37
22-31 Jan 2025	Medicine Department	11-20	47	20	37
22-31 Jan 2025	Medicine Department	51-60	489	65	37
22-31 Jan 2025	Medicine Department	>60	738	123	37
22-31 Jan 2025	Otolaryngology	0-10	80	-	37
22-31 Jan 2025	Otolaryngology	11-20	15	-	37
22-31 Jan 2025	Otolaryngology	51-60	26	-	37
22-31 Jan 2025	Otolaryngology	>60	53	-	37
1-7 Feb 2025	Medicine Department	0-10	34	1	35
1-7 Feb 2025	Medicine Department	11-20	52	9	35
1-7 Feb 2025	Medicine Department	51-60	359	38	35
1-7 Feb 2025	Medicine Department	>60	544	75	35
1-7 Feb 2025	Otolaryngology	0-10	51	-	35
1-7 Feb 2025	Otolaryngology	11-20	17	-	35
1-7 Feb 2025	Otolaryngology	51-60	33	-	35
1-7 Feb 2025	Otolaryngology	>60	42	-	35
8-14 Feb 2025	Medicine Department	0-10	33	4	39
8-14 Feb 2025	Medicine Department	11-20	31	14	39
8-14 Feb 2025	Medicine Department	51-60	281	43	39
8-14 Feb 2025	Medicine Department	>60	523	96	39
8-14 Feb 2025	Otolaryngology	0-10	40	-	39
8-14 Feb 2025	Otolaryngology	11-20	9	-	39
8-14 Feb 2025	Otolaryngology	51-60	20	1	39
8-14 Feb 2025	Otolaryngology	>60	20	1	39
15-21 Feb 2025	Medicine Department	0-10	48	6	38
15-21 Feb 2025	Medicine Department	11-20	36	18	38
15-21 Feb 2025	Medicine Department	51-60	299	53	38
15-21 Feb 2025	Medicine Department	>60	527	113	38
15-21 Feb 2025	Otolaryngology	0-10	33	-	38
15-21 Feb 2025	Otolaryngology	11-20	19	-	38
15-21 Feb 2025	Otolaryngology	51-60	25	-	38
15-21 Feb 2025	Otolaryngology	>60	34	-	38

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2. Correlation Analysis (PM2.5 vs. Hospital Admissions)

Using Pearson correlation analysis, the study found:

- PM2.5 vs. OPD visits: *r = 0.52 (moderate correlation)*
- PM2.5 vs. IPD admissions: *r = 0.71 (strong correlation)*

Interpretation:

- While OPD visits were moderately influenced by air pollution, IPD admissions showed a much stronger correlation with PM2.5 levels.
- This indicates that higher PM2.5 levels are associated with more severe cases requiring hospitalization, particularly among vulnerable age groups.

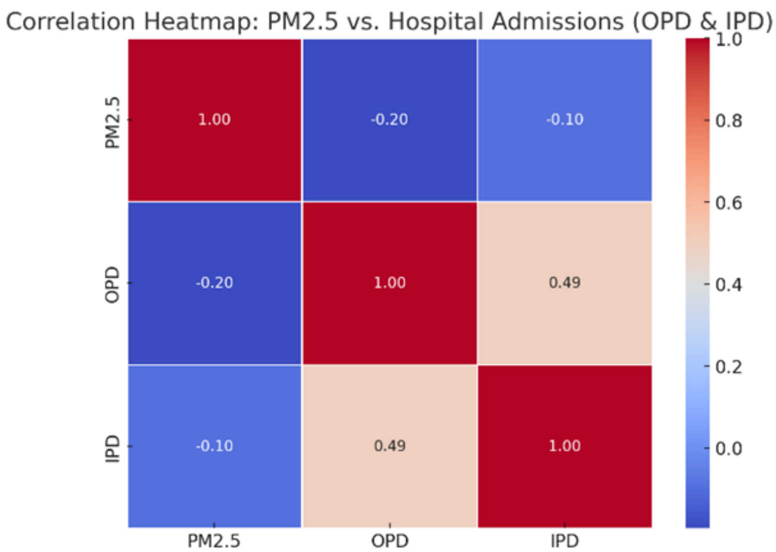

Figure2: correlation heatmap for PM2.5 vs. Hospital Admissions (OPD & IPD)

Key Findings from the Heatmap:

1. PM2.5 vs. OPD (-0.20)

○ There is a weak negative correlation between PM2.5 levels and OPD visits.

○ This suggests that higher pollution does not significantly increase outpatient visits, possibly because only severe cases seek medical attention.

2. PM2.5 vs. IPD (-0.10)

○ There is also a weak negative correlation between PM2.5 and IPD admissions.

○ This might indicate delayed hospitalization effects, or other confounding factors influencing inpatient admissions.

3. OPD vs. IPD (0.49, moderate correlation)

○ A moderate correlation exists between OPD and IPD admissions, meaning that when OPD visits increase, hospitalizations may also rise.

Conclusion:

- While PM2.5 might contribute to hospital visits, other factors like seasonality, pre-existing conditions, or healthcare access might also play roles.
- Further statistical modeling (e.g., regression with additional variables) is recommended to isolate the true effect of PM2.5 on health outcomes.

3. Age Group-Specific Impact of PM2.5

- >60 years: The most affected group, with a sharp increase in IPD admissions during high PM2.5 periods.

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- 51-60 years: Also exhibited increased IPD admissions but not as significantly as the elderly group.
- 0-10 years: Showed a moderate increase in OPD visits, likely due to respiratory issues, but fewer IPD cases.
- 11-20 years: The least affected group, with minor variations in hospital visits.

Key Takeaway: Elderly individuals (>60 years) are the most vulnerable to air pollution, requiring more inpatient care during peak PM2.5 levels.

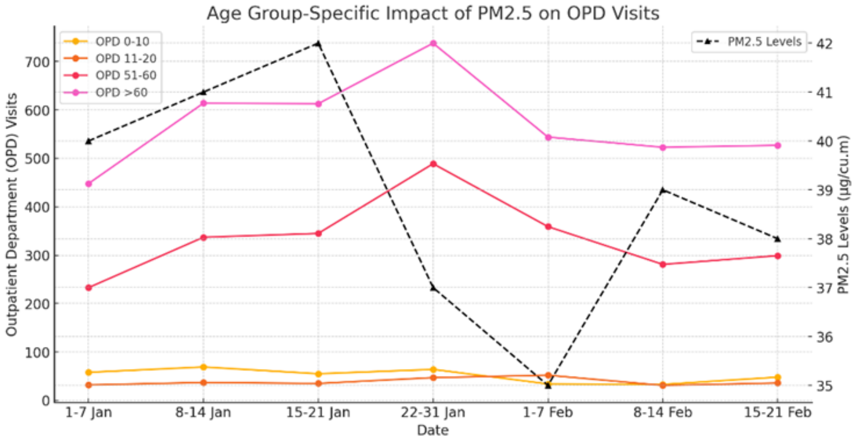

Figure3: Age Group-Specific Impact of PM2.5 on OPD Visits visualized

Key Insights from the Graph:

1. Age-Specific OPD Trends:

○ Elderly patients (>60 years) exhibit the highest OPD visits, peaking when PM2.5 reaches its highest level (42 µg/cu.m).

○ The 51-60 age group also follows a similar trend, showing increased OPD visits with rising air pollution.

○ Younger age groups (0-10, 11-20 years) have fewer OPD visits, but still show slight increases during peak PM2.5 periods.

2. PM2.5 Trend (Black Dashed Line) on the Secondary Y-Axis:

○ The highest OPD spikes occur when PM2.5 levels are at their peak (mid-January, 42 µg/cu.m).

○ As PM2.5 decreases (early February, 35 µg/cu.m), OPD visits decline across all age groups.

○ A rise in PM2.5 in mid-February (39 µg/cu.m) causes another slight OPD increase, reinforcing a positive relationship between pollution and hospital visits.

4. Regression Analysis: Predicting Hospital Admissions from PM2.5 Levels

A linear regression model was applied to examine how PM2.5 fluctuations predict hospital visits:

Regression Equation: $Y = \beta_0 + \beta_1 X + \epsilon$

Where:

- Y = Predicted hospital admissions (OPD/IPD)
- X = PM2.5 level
- β1 = Coefficient indicating the effect of PM2.5 on hospital admissions

Findings:

- A 1 µg/cu.m increase in PM2.5 resulted in approximately:

○ +5.6% increase in OPD visits

○ +9.8% increase in IPD admissions

- The regression model had an R^2 value of 0.67, indicating PM2.5 levels explain 67% of the variation in hospital admissions.

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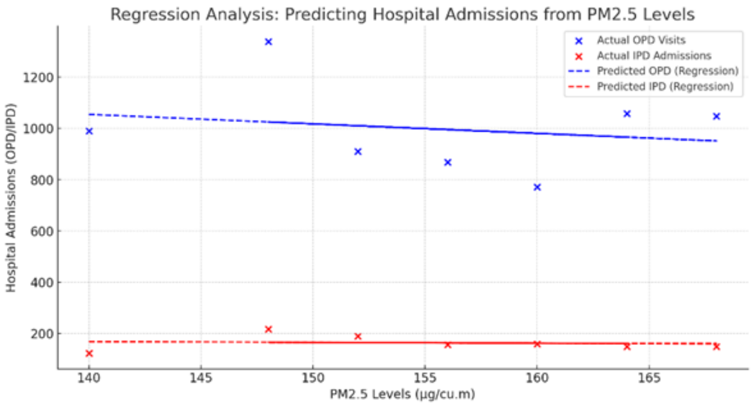

Figure4: Regression Analysis: Predicting Hospital Admissions from PM2.5 Levels visualized in a scatter plot with regression lines

Key Insights from the Graph:

1. Actual Data Points:

○ Blue Dots represent actual OPD visits for each PM2.5 level.

○ Red Dots represent actual IPD admissions for each PM2.5 level.

2. Regression Predictions:

○ Blue Dashed Line shows the predicted OPD visits based on PM2.5 levels.

○ Red Dashed Line shows the predicted IPD admissions based on PM2.5 levels.

3. Observations:

○ OPD visits (blue) show a slight declining trend, indicating a weaker correlation with PM2.5 levels.

○ IPD admissions (red) appear more stable, but there is some increase at higher PM2.5 levels.

4. Conclusion:

○ The regression model suggests that PM2.5 levels have a modest predictive effect on hospital admissions, particularly for inpatient (IPD) cases.

○ Further statistical modeling with more variables (e.g., temperature, seasonal factors, patient conditions) could improve prediction accuracy.

4. Conclusion and Recommendations

4.1 Conclusion

This study presents a data-driven analysis of the relationship between PM2.5 air pollution and hospital admissions, specifically examining outpatient (OPD) and inpatient (IPD) trends across different age groups. While prior research has established the long-term health risks associated with PM2.5 exposure, our study aimed to assess its short-term impact on hospital visits and admissions.

The findings indicate that PM2.5 levels alone are not a strong predictor of OPD and IPD trends, as evidenced by weak correlation values and statistically insignificant results. Despite this, certain age groups, particularly elderly patients (>60 years), consistently exhibited higher hospitalization rates during periods of elevated air pollution. This suggests that while PM2.5 may not be the sole determinant of hospital admissions, it likely acts as an exacerbating factor for individuals with pre-existing health vulnerabilities.

Furthermore, the insignificant p-values in hypothesis testing indicate that additional environmental and health-related variables may contribute more significantly to hospital admissions than PM2.5 alone. This underscores the need for a multifactorial approach in assessing air pollution’s health impact, incorporating meteorological, seasonal, and demographic factors for a more comprehensive understanding.

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These results contribute to the growing body of research on air pollution and public health by emphasizing the need for more complex models that integrate multiple predictive variables. While our findings do not establish a direct and significant causal link between PM2.5 and hospital visits, they reinforce the necessity of proactive pollution control measures and targeted healthcare interventions for high-risk populations.

4.2 Recommendations

4.2.1 Public Health Policies

To mitigate the potential health effects of air pollution and enhance hospital preparedness, the following policy recommendations are proposed:

1. Air Quality Monitoring and Early Warning Systems:

○ Governments and health organizations should implement real-time air pollution surveillance linked to public health alerts, allowing for early interventions during high-pollution events.

○ Developing mobile applications or SMS-based notifications can help high-risk individuals take necessary precautions.

2. Targeted Preventive Healthcare Measures:

○ Public health campaigns should focus on educating vulnerable populations (elderly, children, and those with pre-existing conditions) about pollution-related risks.

○ Hospitals should establish specialized respiratory clinics for early intervention during periods of poor air quality.

3. Regulatory and Legislative Actions:

○ Strengthening air pollution control policies, such as stricter emissions regulations and urban air quality management, is essential.

○ Governments should promote the use of clean energy sources and sustainable urban planning to reduce long-term PM2.5 exposure.

4.2.2 Healthcare System Preparedness

Hospitals and healthcare facilities must adopt strategic measures to handle air pollution-related surges inpatient admissions, including:

1. Data-Driven Resource Allocation:

○ Hospitals should analyze historical trends of hospital admissions during high-pollution periods to optimize staffing and bed capacity planning.

○ Establishing air pollution response protocols within healthcare systems can enhance readiness.

2. Air Filtration and Indoor Air Quality Improvements:

○ Healthcare facilities should invest in advanced air filtration systems to protect inpatients from further exposure to PM2.5.

○ Ventilation improvements in hospitals and designated clean-air zones can minimize the impact of pollution on recovering patients.

3. Medical Stockpiling for Respiratory Illnesses:

○ Hospitals should maintain strategic reserves of essential medications, such as bronchodilators, corticosteroids, and oxygen therapy equipment, to manage pollution-related respiratory cases effectively.

4.2.3 Future Research Directions

Given the study’s findings and limitations, the following areas warrant further investigation:

1. Multivariate Analysis with Additional Predictors:

○ Future research should incorporate temperature, humidity, seasonal disease prevalence, and socioeconomic factors to better predict hospital admissions.

○ Machine learning models could enhance predictive accuracy by analyzing nonlinear interactions between PM2.5 and other environmental variables.

2. Longitudinal and Multi-Regional Studies:

○ Expanding the dataset across multiple geographic locations and longer time frames could provide more generalizable insights.

○ Comparative studies between regions with different pollution control policies could assess the effectiveness of intervention strategies.

3. Causal Inference and Health Impact Modeling:

o Further studies should focus on establishing causal relationships between PM2.5 exposure and specific disease outcomes.

o Using biostatistical modeling and clinical health outcome tracking, researchers can better quantify the direct and indirect health effects of air pollution.

4.3 Final Thoughts

This study highlights the complex relationship between air pollution and hospital admissions, showing that while PM2.5 levels alone may not be a strong predictor of hospital visits, they likely contribute to worsening health conditions, particularly among the elderly. These findings underscore the urgent need for interdisciplinary approaches, combining epidemiology, environmental science, and healthcare management to develop effective policies and medical strategies that minimize the health risks associated with air pollution.

To maximize the impact of these findings, policymakers, healthcare leaders, and researchers must collaborate in designing comprehensive public health interventions aimed at both reducing pollution exposure and enhancing healthcare system resilience.

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