Original Article The correlation between respiratory infectious diseases, air pollution, and meteorological factors in Jinan, China from 2021 to 2023

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Abstract: Objective: To investigate the epidemiological patterns of respiratory infectious diseases in Jinan from 2021 to 2023 and to elucidate the relationship among these diseases, meteorological factors, and air pollution. Methods: We conducted a retrospective analysis of outpatient and inpatient data related to respiratory infectious diseases recorded by the Jinan Health Care Development Center from 2021 to 2023. Additionally, we gathered data on outdoor air pollution indicators and meteorological variables from 14 environmental monitoring stations in Jinan. A generalized Poisson regression model for time series analysis was employed to examine the correlation between meteorological factors, air pollution levels, and hospitalization rates for respiratory infectious diseases. Results: From 2021 to 2023, the daily average concentrations of atmospheric pollutants sulfur dioxide (SO₂), nitrogen dioxide (NO₂), and carbon monoxide (CO) adhered to the national air quality standards, while the daily average concentrations of inhalable particulate matter (PM₁₀) and fine particulate matter (PM₂₅) exceeded the national first-class limits. The daily average concentration of ozone $(0₂)$ surpassed the national secondary standard, indicating severe O_3 pollution. Regarding respiratory disease patients, the relative risk (RR) values of PM₁₀, PM₂₅, SO₂, NO₂, and CO were highest at a lag of 07 d. Compared to other age groups, PM_{2.5}, SO₂, NO₂, and CO had a more significant impact on respiratory disease treatment on children aged 0-12, while PM_{10} significantly affected individuals aged 60 and above. In the single pollution model, RR values corresponding to PM₁₀, PM₂₅, SO₂, CO, and NO₂ were 1.008, 1.058, 1.224, 1.405, and 1.102 respectively on lag07d. The multi-pollutant model maintained the positive relationship between the total hospitalization frequency of respiratory diseases and CO, NO₂, SO₂, PM₁₀, and PM_{2.5}. Conclusion: Our study found a strong, positive correlation with a lag effect between total number of hospitalizations for common respiratory diseases and pollutants CO, NO₂, SO₂, PM₁₀, and PM_{2.5} in the examined sample.

Keywords: Outdoor air pollution, meteorological factors, respiratory infectious diseases, number of hospital visits, correlation

Introduction

Environmental risk factors play a pivotal role for human health. Among these, outdoor air pollution stands as a prominent threat. According to the 2019 Global Burden of Disease (GBD) study, outdoor air pollution ranks as the fourth leading cause of mortality worldwide, accounting for approximately 6.67 million deaths annually, thereby eliciting unprecedented societal concern regarding its detrimental health effects [1]. Extensive research by international scholars has highlighted the adverse impact of air pollution on numerous non-communicable diseases, such as lung cancer, stroke, ischemic heart disease, respiratory infections, and chronic obstructive pulmonary disease [2-7].

China, in recent years, has undergone rapid industrialization, which has unfortunately been accompanied by a marked deterioration in air quality. Among the various outdoor air pollutants, haze poses the most significant challenge, primarily comprising particulate matter (PM $_{10}$) and PM_{25} [8]. Specifically, inhalable particulate matter (PM_{10}) predominantly accumulates in the upper respiratory tract, whereas fine particulate matter (PM), with its smaller size, can penetrate deeper into the body, reaching the trachea, alveoli, and even circulating in the bloodstream, thereby predisposing individuals to cardiovascular and respiratory diseases [9-11].

For many years, numerous studies have documented air quality findings across various cities and regions in China. Given the disparity in meteorological conditions and air pollution levels across these areas, their health impacts may vary significantly [12]. Jinan, as the provincial capital of Shandong Province, functions as a political, cultural, transportation, and economic hub, and is also emblematic of severe air pollution challenges in North China. Since the inception of China's Clean Air Action in 2013, Jinan has made notable strides in mitigating key air quality pollutants [13].

Nevertheless, prior research on Jinan's air pollution overlooked the intricate interplay between air quality, meteorological factors, and respiratory infectious diseases [14]. Furthermore, during the COVID-19 pandemic, cities experienced enforced lockdowns, creating a relatively "simplified" living environment for urban dwellers.

Hence, this study endeavored to elucidate the temporal variations of outdoor air pollutants in Jinan from 2021 to 2023 and the influence of meteorological factors on respiratory infectious disease incidence. Our findings aimed to inform future assessment of the disease burden associated with outdoor air pollution and assist relevant authorities in devising effective management strategies.

Materials and methods

Data source

Data on respiratory infectious diseases: Retrospective data on outpatient and inpatient cases of respiratory infectious diseases in Jinan Health Care Development Center, spanning from January 1, 2021 to December 31, 2023, were electronically extracted from the medical record system. These cases were categorized according to the 10th revision of the International Classification of Diseases (ICD-10). The study protocol was endorsed by the Ethics Committee of Jinan Health Care Development Center, adhering to the principles outlined in the Helsinki Declaration. Given the retrospective nature of the study, the ethics

committee granted an exemption from informed consent.

Patients with ICD-10 codes falling within the range J00-J99 were included, encompassing conditions such as acute upper respiratory tract infections, acute and chronic tracheobronchitis, pneumonia, influenza, tuberculosis, acute tonsillitis, pharyngitis, laryngitis, asthma, and related disorders. Cases attributed to surgical procedures, accidents, or other non-natural causes were excluded. In total, 20,148 patients were included in this study, with a gender distribution of 9,772 females and 10,376 males.

Air pollution monitoring data: Air pollution data for Jinan City during the same period frame were systematically compiled. The data came from the daily data of 14 environmental monitoring sites of Jinan Bureau of Ecological Environment. In this study, the average value of 14 monitoring sites was taken as the representative of the air quality level of Jinan City. Air pollution indicators included: inhalable PM_{10} , fine PM_{2.5}, carbon monoxide (CO), ozone $(0, 0)$, nitrogen dioxide $(NO₂)$ and sulfur dioxide $(SO₂)$.

Meteorological data: Concomitant meteorological data for Jinan City were also gathered and organized. The source of these meteorological indicators was the Jinan Meteorological Bureau. The variables included in the study were relative humidity, average daily temperature, minimum temperature, and maximum temperature, all of which were deemed relevant to the analysis.

Generalized additive model (GAM) analysis

To investigate the associations between PM pollution and daily outpatient visits for various respiratory diseases, we integrated daily outpatient counts, air pollution indices, and meteorological parameters by date. This time series approach is widely employed in assessing the acute health impacts of air pollution, offering the advantage of repeatedly observing health effects among a consistent study population under varying exposure conditions. Consequently, factors that remain relatively stable over the study period, such as age, gender, smoking habits, hypertension status, and socioeconomic factors, are inherently controlled for, minimizing confounding effects.

Given that daily outpatient events are independent, low-probability occurrences that approximate a Poisson distribution, and the nonlinear nature of the relationship between outpatient counts and explanatory variables, we employed the GAM as our primary analytical tool. Additionally, to address the common issue of "overdispersion" in outpatient counts, we integrated the quasi-Poisson distribution within the GAM framework. This Poisson regressionbased GAM was designed to explore the intricate relationships between outdoor air pollutants, meteorological factors, and outpatient visits for respiratory diseases. The model constructed in this article was:

$$
log[E(Y_j)] = a + b_j X_j + \sum_{j=0}^{m} S_j(Z_j)
$$
 (1)

The GAM model is as follows:

$$
log[E(Yt)] = a + biZt + s(time, 7) + s(T, 3) + s(RH, 3)
$$

+
$$
DOMt + \text{holiday}t + \text{Influenza}
$$
 (2)

Among them, the expected number of outpatient visits on day (t) is denoted by ${E}(Y_t)$ in person-times, with (α) representing the intercept. The pollutant concentration on day (t) is represented by (Z_{t}) , measured in units of (µg/ m^3). The cubic spline function is denoted by (S), with degrees of freedom represented by (df). Time (T) is a temporal variable in years, used to control for long-term and seasonal trends in the time series data. Other meteorological factors include temperature (T), relative humidity (RH). The categorical indicator variable for "which day of the week" is denoted by (DOW), the indicator variable for "holiday effect" by (Holiday), and the indicator independent variable for "influenza outbreak week" by (Influenza).

To refine the model, we adjusted it using the natural cubic spline function (ns) and incorporated the influence of meteorological factors and day-of-week (DOW) effects as categorical variables. The fundamental modeling strategy employed is:

(1) Incorporate a cubic spline smoothing function of time into the model to account for both the long-term trend and seasonal variation in daily outpatient visits. (2) In constructing the model for this study, the selection of the degrees of freedom (df) for the time smoothing function is paramount. This process was facilitated by utilizing the partial autocorrelation function (PACF). A range of 4-12 df/year was explored to fit the time trend, sequentially testing the models and plotting PACF graphs with a 30-day lag. When the absolute values of the first two lags in these plots fell below 0.1, we deemed the model to have effectively controlled for autocorrelation. If this criterion was not met, an autoregressive term with a maximum lag of 7 days was introduced to refine the model [15]. Ultimately, we opted for 7 df/year to effectively manage seasonal and long-term temporal trends. (3) To control for temporal patterns within the time series, we introduced the dummy variable DOW into the model. This allowed us to account for the "day of the week effect", wherein outpatient visits may exhibit periodic fluctuations due to factors such as weekends. (4) Furthermore, the "holiday" indicator variable was incorporated into the baseline model to mitigate the potential "holiday effect", where changes in outpatient visits may occur due to various reasons associated with holidays. (5) In the fundamental model, we incorporated a dummy variable indicating "flu outbreak week" to regulate the interplay between hospital visits and influenza epidemics. This variable is defined by comparing weekly influenza visits to the annual average; if the weekly count exceeds 75% of this average, it is classified as an outbreak week, otherwise, a non-outbreak week. (6) To delve into the associations among PM pollution, outpatient visits, and seven other factors, we augmented the model with two crucial variables: RH and T. Notably, the relationship between outpatient volumes and meteorological parameters is nonlinear, necessitating the application of a cubic spline smoothing function. Here, we set the degrees of freedom for humidity and temperature at 3. Existing research underscores the health impacts of temperature, with a lag effect spanning at least 10 days [16], whereas no such delayed effect has been observed for relative humidity [17]. Consequently, our analysis considers RH and the average T over the 14-day outpatient period.

Statistical analysis

The Excel software was employed to construct a comprehensive database, incorporating all gathered outdoor air pollution indices, meteorological parameters, and hospital patient records. The dataset underwent rigorous preprocessing, including sorting, detection of logical inconsistencies, and verification of missing values.

Statistical analyses were performed utilizing SPSS 22.0 software. The distribution of all indicators approximated normality and were thus presented as mean ± standard deviation (*_ x*±*s*), complemented by descriptive statistics including P25, P50, and P75 percentiles, and the minimum and maximum values.

To investigate the correlations between hospitalization rates for respiratory infectious diseases, meteorological factors, and the significance level was set at α = 0.05 (two-tailed). Spearman's correlation analysis was selected for this purpose, with statistical significance denoted by P<0.05.

Furthermore, a GAM based on Poisson distribution was utilized to quantify the relationships between outdoor air pollutants, meteorological variables, and the number of patients diagnosed with respiratory infectious diseases.

Results

Descriptive analysis of basic data

Between January 1, 2021 and December 31, 2023, Jinan's annual daily mean temperature was 16.12°C, ranging from -4.50°C to 34.00°C. The daily average relative humidity stood at 58.40%, with a wide variation from 26.07% to 397.41%. For our country, 150 $g/m³$ was the second level.

Regarding air quality, the daily average concentration of PM₁₀ was 109.06 μ g/m³, falling between the national first (50 μ g/m³) and second (150 µg/m^3) air quality standards. Similarly, $PM_{2.5}$ concentrations averaged 53.29 μg/m³, positioned between the primary (35 μg/ m³) and secondary (75 μ g/m³) standards. Concentrations of $SO₂$ and $NO₂$ complied with national first-class standards. However, O_3 levels, with a daily average of $174.88 \mu g/m^3$, significantly exceeded the national secondary standard of $160 \mu g/m^3$, indicating a relatively high level of pollution from this pollutant.

In terms of air quality rankings among 168 key cities nationwide, Jinan ranked 157th in 2021 and 158th in 2023, with 182 and 227 days of good air quality, respectively.

During the study period, a total of 170,014 outpatient and inpatient visits for respiratory infectious diseases were recorded, averaging 465.82 visits per day (ranging from 73 to 951 visits/day). Among these patients, 50.56% (85,957) were male, and 49.44% (84,057) were female. Age-wise, 21.09% (35,852) were ≤12 years old, 53.69% (91,288) were between 13 and 60 years old, and 25.22% (42,874) were ≥60 years old. These findings are summarized in Table 1.

Spearman correlation analysis

Our analysis elucidates a strong interdependence among various air pollutants and meteorological factors. Specifically, PM_{10} and PM_{25} exhibit a significant negative correlation (P<0.01), indicating a mutual influence in their concentrations. Likewise, O₂ displays a positive correlation with temperature (P<0.01), suggesting that warmer conditions favor $O₃$ formation. In contrast, O_3 negatively correlates with PM₁₀ and PM_{2.5} (P<0.01), likely due to their competing chemical pathways.

Furthermore, PM_{10} is positively correlated with $NO₂$ and CO (P<0.05), emphasizing the interconnectedness of pollutant sources and their atmospheric behavior. Notably, the daily maximum temperature significantly influences this relationship. Additionally, $SO₂$ and $PM₂₅$ are positively correlated (P<0.05), with the daily average temperature having a marked impact on this association.

Temperature and daily average relative humidity also demonstrate a positive correlation (P<0.05), with temperature exhibiting the strongest link among the analyzed variables. The comprehensive results of this Spearman correlation analysis are presented in Table 2.

Time trend of PM2.5 and respiratory infectious disease hospital visits

Figure 1 depicts a notable seasonal pattern in PM_{25} concentrations in Jinan during 2021 and 2023, with peak levels observed in winter (December to January) and troughs in summer (May to August). However, the seasonal trend in $PM_{2.5}$ concentrations did not mirror a significant

Indicator		\overline{x} ±s	P_{25}	$P_{\underline{50}}$	P_{75}	Min	Max
Air pollution	PM_{10} (µg/m ³)	109.06±94.51	53.26	102.81	148.98	9.89	333.05
	PM_{25} (µg/m ³)	53.29±36.77	21.56	44.43	73.91	7.68	183.84
	$SO2(\mu g/m3)$	15.01±9.88	7.67	13.93	20.59	4.05	51.02
	$NO2$ (µg/m ³)	45.02±31.28	21.48	42.80	62.33	8.12	139.66
	$O_{\rm s}$ (µg/m ³)	174.88±129.56	76.73	160.95	248.31	9.80	542.63
	$CO \ (mg/m3)$	1.41 ± 0.96	0.66	1.35	2.03	0.38	4.28
Meteorological factor	Daily minimum temperature (°C)	22.45±11.37	11.50	22.00	31.00	-1.00	38.00
	Daily minimum temperature (°C)	11.46±10.40	1.00	12.00	21.00	-9.00	31.00
	Daily average temperature (°C)	16.17 ± 10.52	5.75	17.00	25.00	-4.50	34.00
	Daily average relative humidity (%)	58.45±35.68	30.17	55.39	84.77	26.07	97.41
Number of hospital visits	Total number of hospital visits	462.84±393.00	197.00	393.00	627.00	73.00	951.00
	Male	233.48±181.65	102.00	189.00	325.00	57.00	629.00
	Female	231.33±184.73	100.00	194.00	312.00	64.00	644.00
	\leq 12 years	98.23±89.22	38.00	75.00	130.00	43.00	394.00
	12-60 years	250.10±208.84	98.00	200.00	340.00	53.00	741.00
	≥ 60 years	117.48±99.67	46.00	89.00	156.00	46.00	419.00

Table 1. Descriptive statistical results of outdoor air pollution indicators, meteorological indicators and daily number of hospital visits for respiratory infectious diseases in Jinan from 2021 to 2023

Note: PM₁₀: inhalable particulate matter; PM₂ =: fine particulate matter; SO₂: sulfur dioxide; NO₂: nitrogen dioxide; O₃: ozone; CO: carbon monoxide.

corresponding trend in the frequency of hospital visits for respiratory infectious diseases. Both metrics exhibited a similar seasonal variation, with the lowest incidence occurring from May to August and peaking from December to February.

Time trend of PM₁₀ and respiratory infectious disease hospital visits

Analogously, Figure 2 illustrates a distinct seasonal trend in PM_{10} concentrations in Jinan over the same time frame, with the highest concentrations in winter (December to January) and the lowest in summer (May to August). Despite this clear seasonal variation in PM_{10} levels, no significant correlation was observed between its trend and the frequency of hospital visits for respiratory infectious diseases. Similar to $PM_{2.5}$, the incidence of respiratory infectious diseases was lowest during May to August and peaked during December to February.

Analysis results of GAM

In order to test the impact of co-pollutants in the atmosphere $(SO_2, NO_2, CO$ and O_3) on the estimated health effects of PM pollution, we employed a series of single-pollutant models, each augmented with an additional pollutant. Subsequently, a multi-pollutant model was fitted to determine the robustness of the individual PM effects on hospital visits for respiratory diseases. We conducted a comprehensive analysis of the lagging effects between health outcomes and particulate pollutants, considering lags from lag0 (pollution day) to lagN (N days after exposure), as well as cumulative lags (e.g., lag01, lag02, lag03) representing the average impact over 1 to N days. Setting the reference concentration for air pollution, we consistently 0 μ g/m³, acknowledging its theoretical minimum and facilitating interpretation. Based on the constructed GAMs, we estimated the relative risk (RR) and 95% confidence interval (CI) for respiratory disease visits, associated with a 10 μg/m³ increase in PM₁₀ and PM_{2.5} concentrations.

Single pollutant model: Figure 3 presents the estimated impact of a 10 μ g/m³ increase (or 1 mg/m3 for CO) in various air pollutants on the total number of hospitalizations for respiratory diseases in Jinan City from 2021 to 2023. Significant adverse effects were observed for PM_{25} , SO₂, and CO on lags ranging from lag0 to lag7 (inclusive), with cumulative lags (lag01 to lag07) also exhibiting significant impacts. Notably, the strongest effect for PM_{25} , SO₂, and CO was observed at lag7, with corresponding RR values were of 1.058, 1.224, and 1.405,

Variable	PM_{10}	$PM_{2.5}$	SO ₂	NO ₂	O ₃	CO	Daily maximum temperature	Daily minimum temperature	Daily average temperature
$PM_{2.5}$	$0.183*$								
SO ₂	$0.139*$	$0.135*$							
NO ₂	$0.129*$	0.025	0.017						
O ₃	$-0.188**$	$-0.223*$	$-0.183*$	$-0.151*$					
CO	$0.112*$	0.068	0.113	$0.054*$	$-0.155*$				
Daily maximum temperature	$-0.265**$	$-0.277**$	$-0.254**$	$-0.242**$	$0.334**$	$-0.246**$			
Daily minimum temperature	$-0.242**$	$-0.257**$	$-0.261**$	$-0.257**$	$0.361**$	$-2.262**$	$0.981**$		
Daily average temperature	$-0.253**$	$-0.265**$	$-0.257**$	$-0.2354**$	$0.372**$	$-0.271**$	$0.981**$	$0.989**$	
Daily average relative humidity	-0.025	-0.021	0.029	-0.038	0.085	0.022	$0.119*$	$0.113*$	$0.109*$

Table 2. Correlation analysis between outdoor air pollution and meteorological factors in Jinan City from 2021 to 2023

Note: *indicated *P*<0.01; **indicated *P*<0.05; PM₁₀: inhalable particulate matter; PM_{2.5}: fine particulate matter; SO₂: sulfur dioxide; NO₂: nitrogen dioxide; O₃: ozone; CO: carbon monoxide.

Figure 1. Time trend of PM_{2.5} and number of hospital visits for respiratory infectious diseases in Jinan from 2021 to 2023. A: Time trend of PM $_{2.5}^-$ in Jinan from 2021 to 2023. B: Time trend of number of hospital visits for respiratory infectious diseases in Jinan from 2021 to 2023.

Figure 2. Time trend of PM₁₀ and number of hospital visits for respiratory infectious diseases in Jinan from 2021 to 2023. A: Time trend of PM $_{10}^{7}$ in Jinan from 2021 to 2023. B: Time trend of number of hospital visits for respiratory infectious diseases in Jinan from 2021 to 2023.

respectively. For PM_{10} , significant effects were seen on lag2 and cumulative lags from lag02 to lag07, with the highest RR at lag7. Similarly, NO₂ had a notable effect across lags 0, 3 to 7, and cumulative lags 01 to 07, peaking at lag7 with an RR of 1.102 (95% CI: 1.082-1.121). Conversely, no significant association was found between $O₂$ (8-hour average) and respiratory hospitalizations across various lag periods.

Further examination of age-specific impacts of PM_{25} on respiratory hospitalizations, as depicted in Figure 4, reveals that children aged 0-12 years were particularly vulnerable, with significant effects observed on lags 0, 5 to 7, and cumulative lags 1 to 7. In the 13-59 age group, significant effects were noted on lags 2-3, 5-7, and cumulative lags 02 to 07. Among the elderly (≥60 years), significant effects were observed on lags 2-3, 6-7, and cumulative lags 05 to 07, indicating age-dependent susceptibilities to $PM_{2.5}$ exposure.

Figure 5 illustrates the differential impact of $PM_{2.5}$ on respiratory disease hospitalizations by gender. A clear pattern emerges, indicating that women are more adversely affected by $PM_{2.5}$ exposure than men. For women, $PM_{2.5}$ exhibits a significant cumulative lag effect on respiratory emergency visits, with the strongest influence observed at lag07. In contrast, for men, the detrimental effects of $PM_{2.5}$ on respiratory emergency visits are evident on days 0-lag1, lag2-lag5, and cumulative lags 02-lag07, peaking at lag07. Notably, the cumulative lag effect surpasses the single-day lag effect for both genders.

Multi-pollutant model: To discern the individual and combined effects of multiple pollutants, we selected the pollutant with the most pronounced effect at lag07 to fit a dual-pollutant model. This approach allowed us to assess the stability of our model results, as detailed in Table 3. Given the high correlation between $PM_{2.5}$ and PM_{10} (r = 0.86), they were not simultaneously included in the dual-pollutant model

Respiratory infectious diseases and air pollution in Jinan

Figure 3. Influence of air pollution on total number of hospital visits for respiratory diseases. A: Influence of PM $_{2.5}$ on total number of hospital visits for respiratory diseases. B: Influence of PM₁₀ on total number of hospital visits for respiratory diseases. C: Influence of SO₂ on total number of hospital visits for respiratory diseases. D: Influence of NO₂ on total number of hospital visits for respiratory diseases. E: Influence of CO on total number of hospital visits for respiratory diseases. F: Influence of O₃ on total number of hospital visits for respiratory diseases. Note: RR: relative risk; PM₁₀: inhalable particulate matter; PM₂₅: fine particulate matter; SO₂: sulfur dioxide; NO₂: nitrogen dioxide; O₂: ozone; CO: carbon monoxide.

to avoid multicollinearity. Our findings reveal that the inclusion of additional pollutants did not significantly alter the effect estimates of SO₂ and NO₂ on the total number of respiratory disease hospitalizations.

Discussion

Jinan, a representative city in northern China utilizing central heating, experienced air quality issues from 2021 to 2023. During this period, daily average concentrations of CO and SO₂ surpassed national first-level standards, while $PM_{2.5}$ and PM₁₀ fell between the first and second levels, and $O₃$ exceeded the second-level

standard. Notably, O₂ and PM emerged as the primary pollutants of concern, with PM_{10} pollution exceeding that of $PM_{2.5}$.

Using medical records from respiratory infectious disease patients treated in a local hospital over the same timeframe, this study employed a GAM model based on Poisson regression to explore the association between respiratory disease hospitalizations and air pollution exposure. Our findings underscore that not only O_3 but also particulate pollutants like PM $_{2.5}$ and PM_{10} significantly impact the total number of respiratory disease visits, exhibiting an approxi-

Figure 4. Influence of PM_{2.5} on total number of hospital visits for respiratory diseases in different age groups. Note: RR: relative risk; PM_{2} : fine particulate matter; YO: years old.

Figure 5. Influence of PM_{2.5} on total number of hospital visits for respiratory diseases in different age groups. Note: RR: relative risk; CO: carbon monoxide.

mately linear non-threshold relationship and a lag effect.

Specifically, the strongest effects of $PM_{2.5}$, PM_{10} , SO₂, NO₂, and CO were observed at a lag of 7 days (lag07). At this point, a 10 μ g/m³ increase in PM_{2.5}, PM₁₀, SO₂, and NO₂, and a 1 mg/m³ increase in CO, were associated with respective RRs of 1.058, 1.008, 1.224, 1.102, and 1.405 for total respiratory disease hospitalizations. The multi-pollutant model maintained the positive correlation between respiratory disease hospitalizations and pollutants like PM_{2.5} and PM₁₀, without altering their relationship. Notably, this model mitigated the significant health effects attributed solely to PM,

aligning with previous findings by Wang et al. [18] and Wang et al. [19].

Our study highlights that children aged 0-12 are particularly vulnerable to $PM_{2.5}$ exposure, experiencing more pronounced impacts than other age groups. This heightened sensitivity can be attributed to their growth and developmental stage, where they are more susceptible to environmental factors compared to adults. Epidemiological evidence supports this, indicating that $PM_{2.5}$ adversely affects children's immune status [20-22], significantly elevating their risk of respiratory diseases.

Conversely, PM_{10} exerts a greater influence on the elderly aged 60 and above. This may stem from the elderly's reduced physical resilience and prevalent underlying health conditions. PM_{10} primarily deposits in the upper respiratory tract, where its accompanying bacteria, viruses, and harmful substances can easily trigger respiratory irritation and lung infections [23, 24]. Domestic and international research consistently demon-

strates a strong correlation between inhalable PM in the air and the number of respiratory outpatient visits [25, 26]. Gu et al. [27] observed a notable increase in respiratory disease mortality with rising $PM_{2.5}$ concentrations. Similarly, Duan et al.'s [28] study in Chengdu revealed that elevated PM_{2.5} levels augment the risk of respiratory illnesses, subsequently boosting outpatient clinic visits. Yin et al. [29], in their Shanghai-based research, concurred, reporting an increase in respiratory clinic visits with daily average $PM_{2.5}$ concentrations.

Cui et al. [30], investigating Jinan City's air pollution from 2014 to 2016, found that PM_{2.5} concentration hikes led to a 0.40% rise in

Model	PM_{25}	SO.	NO.	U_3	CO
Single pollutant model 1.066 (1.055, 1.083)		1.239 (1.195, 1.243)	1.102 (1.082, 1.121)	0.951 (0.942, 0.960) 1.417 (1.341, 1.492)	
$PM_{2.5}$		1.205 (1.162, 1.248)	1.098 (1.067, 1.128)	0.953 (0.933, 0.973) 1.404 (1.314, 1.493)	
SO ₂	1.062 (1.046, 1.078)		1.102 (1.072, 1.131)	0.956 (0.942, 0.969) 1.403 (1.324, 1.481)	
NO ₂	1.051 (1.035, 1.066)	1.227 (1.176, 1.277)			0.961 (0.939, 0.982) 1.401 (1.332, 1.469)
O ₃	1.054 (1.042, 1.066)	1.226 (1.181, 1.271)	1.096 (1.059, 1.133)		1.387 (1.299, 1.475)
CO	1.034 (1.037, 1.030)	1.226 (1.183, 1.269)	1.099 (1.055, 1.142)	0.951(0.934, 0.968)	

Table 3. Dual pollutant model analysis of the influence of air pollution on the total number of hospital visits for respiratory diseases in Jinan City from 2021 to 2023

Note: PM₁₀: inhalable particulate matter; PM₂₅: fine particulate matter; SO₂: sulfur dioxide; NO₃: nitrogen dioxide; O₃: ozone; CO: carbon monoxide.

circulatory system outpatient visits and a 0.28% increase in internal medicine clinic visits. Additionally, PM_{10} concentration increments were associated with a 0.25% increase in circulatory system outpatient cases, though the final sentence concerning outpatient numbers appears incomplete, likely an oversight. Our study aligns with these findings while acknowledging the variability in natural environments, air pollutant compositions, and population demographics across study areas.

It is noteworthy that our analysis did not account for potential confounding variables such as smoking habits, occupation, outdoor activity patterns, lifestyle choices, education levels, and other individual behavioral factors. The exclusion of these factors may introduce bias into our results. Future studies should endeavor to incorporate these variables to provide a more comprehensive understanding of the complex interplay between air pollution and human health. This study is subject to several limitations. Firstly, the data was solely sourced from a single hospital in Jinan City over a threeyear period, inherently introducing potential selection bias and limiting the generalizability of findings. The brevity of the observation period and narrow data scope fail to comprehensively mirror the respiratory disease treatment landscape in Jinan. Secondly, while the GAM accounts for long-term trends, weekday effects, temperature, humidity, and age, it overlooks the influence of individual lifestyle factors and physical health status on respiratory morbidity. The study's relatively short duration may also constrain the applicability of conclusions. To address these limitations, future endeavors should encompass longer-term data collection and more nuanced investigations, encompassing a broader array of possible confounding variables.

In conclusion, in line with prior research, our findings underscore the positive correlation between elevated concentrations of atmospheric pollutants, notably PM₂₅ and PM₁₀, and the heightened risk of respiratory diseases. Consequently, the government of Jinan should devise tailored measures to mitigate environmental pollution and enhance ecological health, taking into account the sources and seasonal variations of air pollution. Additionally, residents are advised to minimize exposure during dusty or hazy weather, utilizing protective gear such as masks, to decrease the inhalation of harmful airborne particles and thereby prevent respiratory illnesses.

Disclosure of conflict of interest

None.

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