

Original Article



Predictions of City-based Respiratory Hospital Visits: Developing and Validating a Machine Learning Model with a Novel Composite Air Pollution Index

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Abstract

Objective City-specific tools for assessing and warning about respiratory disease risks are underdeveloped, limiting effective public health response. This study aimed to develop and validate a novel city-specific prediction framework (WHA_{air}-LSTM) for forecasting daily respiratory outpatient visits by integrating a composite air pollution health index.

Methods Based on over 223.7 million hospital visits across multiple megacities, we constructed and validated a five-level morbidity-driven composite air pollution index (WHA_{air}) for each city using city-specific exposure-response relationships. An LSTM model was built using WHA_{air}, temperature, humidity, and historical visit data to predict next-day visits. The proposed modeling framework was developed with city-level data, and it was externally validated using datasets from other cities.

Results Higher WHA_{air} levels were significantly associated with increased outpatient visits. The model demonstrated excellent predictive performance (Beijing: $R^2 = 0.963$, RMSE = 53.5) and effectively captured visit surges. Excluding WHA_{air} degraded model accuracy (Δ RMSE = +44.1%). The framework maintained robust performance in external validation, confirming its transferability.

Conclusion The WHA_{air}-LSTM framework provides a scalable and practical tool for city-level respiratory disease early warning by bridging environmental monitoring with clinical practice.

Key words: Respiratory disease; Outpatient visits; WHA_{air}; LSTM prediction model

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INTRODUCTION

A combination of atmospheric factors, such as air pollution and weather conditions, can influence the occurrence and progression of respiratory diseases. Compound air pollution (e.g., particulate matter and gaseous pollutants)^[1,2] and non-optimal temperature and precipitation^[3,4] can intensify the hospitalization risk for respiratory diseases—the most atmospheric environment-sensitive condition—through mechanisms such as oxidative stress, inflammation, and direct airway irritation. Owing to a complex atmospheric environment and dense population, city dwellers experience greater exposure to air pollution and an enhanced risk of respiratory diseases^[5]. Therefore, a risk prediction framework for respiratory diseases is essential to support disease prevention and the implementation of emergency medical response^[6,7].

Recent research on risk prediction models for respiratory diseases has been minimal in scope, and existing studies have not adequately supported early warning and emergency response activities for these diseases. First, many previous studies focused on developing indices to identify respiratory disease risks associated with air pollution (e.g., Canada's Air Quality Health Index, AQHI)^[8–21]. However, these indices mainly depend on exposure–response relationships between air pollution and mortality^[8,9,14,17,22], which do not accurately capture the immediate impact of air pollution on respiratory health^[13,18]. Furthermore, these indices are still in development and have not been applied to predict the morbidity risk of respiratory disease. Second, some studies have developed city-level disease prediction models based on single-city datasets, but the lack of external validation limits their generalizability.

Machine learning techniques hold great promise in predictive health analytics. Many studies have attempted to develop risk prediction models for cardiovascular diseases, achieving encouraging predictive results^[23–25]. However, this machine learning-based predictive technology has seen limited application in preventing and controlling atmospheric environment-related disease risks, such as respiratory diseases. Previous studies have examined machine learning methods to predict the air quality index^[26–28]. However, little attention has been accorded to health risk prediction using these indices or assessing their usefulness in forecasting medical needs^[29]. Regarding the models, traditional

statistical approaches such as Autoregressive Integrated Moving Average (ARIMA), Generalized Additive Model (GAM), and Generalized Linear Model (GLM) often struggle to capture temporal dependencies and non-linear trends. In contrast, Long Short-Term Memory (LSTM) networks—a form of recurrent neural network with memory components—provide a robust means of managing time-series data and have been effectively applied to forecast both infectious and non-communicable diseases^[30].

Therefore, this study aimed to develop and validate a novel model framework to predict the acute risk of respiratory diseases associated with daily changes in the atmospheric environment. There are three unique aspects of this study: first, we focused on urban scale instead of broader spatial scales, given the urgency of addressing compound atmospheric impacts on dense population in cities; second, we established a model framework that includes creating a city-level health risk index as well as a machine learning model that incorporates the index to predict respiratory disease risk; third, we performed external validation to verify the robustness of our prediction model.

METHODS

Study Design

We developed a framework to predict city-specific outpatient visits for respiratory diseases, comprising three main steps (Supplementary Figure S1). First, to comprehensively capture air pollution's impact on disease morbidity, we created a five-level index: the Warning for Health Risk of Atmospheric Environment (WHA_{air}). It is based on exposure–response relationships between five air pollutants (PM_{2.5}, PM₁₀, SO₂, NO₂, and O₃) and hospitalization data, which we verified based on its association with outpatient visits for respiratory diseases and their subtypes. Second, we established an LSTM model using the WHA_{air} index, incorporating meteorological factors and historical trends in respiratory disease outpatient visits to predict the immediate risk of respiratory diseases, enabling proactive clinical preparation for air pollution-related patient surges^[31]. Third, to evaluate robustness, we also replicated the entire process using data from other megacities. Specifically, we applied the same method to develop models for Tianjin and Chongqing, and the generalizability of the models was externally confirmed.

Establishment of City-specific WHA_{air}

The WHA_{air} index was developed based on the association between daily air pollution and hospital admission data. We obtained a dataset of daily total hospital admissions in Beijing from January 1, 2013, to December 31, 2018, from the Beijing Municipal Health Commission Information Center. This dataset included medical records from all Grade II and above hospitals in Beijing. Furthermore, we divided the population into children aged 15 years or younger and the elderly aged 65 years or older to create the WHA_{air}, aiming to incorporate the health impact on subpopulations vulnerable to air pollution^[6]. We gathered hourly concentrations of PM₁₀, PM_{2.5}, O₃, SO₂, and NO₂ from the national air quality monitoring sites within Beijing during the same period. Next, we calculated 24-hour average concentrations for PM₁₀, PM_{2.5}, SO₂, NO₂, and the maximum eight-hour moving average for O₃. Additionally, we incorporated meteorological data, including daily temperature and relative humidity, into the model. We applied a conditional Poisson regression model to evaluate the exposure–response relationships between each of the five air pollutants and daily hospital admissions, respectively (see Supplementary Method S1 for details).

By using estimates of exposure–response relationships between five air pollutants and hospital admissions for the general population, children, and the elderly groups, we calculated excess risk with the following equation:

$$ER_j = \sum_{i=1}^5 (e^{\beta_i x_{ij}} - 1) 100\% \quad (1)$$

In this model, ER_j was the total excess risk from all five air pollutants on day j ; β_i was the exposure–response relationship between non-accidental hospital admissions and air pollutant i —here we selected the maximum effect estimates for each pollutant within the optimal lag period to avoid underestimation of related risk; x_{ij} was the daily average concentration of air pollutant i . Using this, we estimated the excess risk for the general population (ER_{total}), children (ER_{ch}), and the elderly (ER_{el}) groups based on population-specific association estimates.

We aimed to establish a five-level index based on the ER values to indicate different levels of disease risk. To set the cutoff points, several key principles were considered: first, it accounts for both the

general population and vulnerable subgroups; second, each index category logically correlates with rising disease risk, so higher index levels indicate greater risk. Accordingly, we customized the cut-off points based on local ER_{total} , ER_{ch} , and ER_{el} . Here, using these ER values, we applied an iterative method, in which different threshold values were applied, to establish a five-level WHA_{air} index and automatically verified the association between the index at each level and the population's hospital outpatient visits. Thresholds were determined when the outpatient visit risk associated with successive levels was distinguished and showed a stepwise increase (Supplementary Method S2 for details).

Specifically, taking Beijing as an example, we collected data on 69,963,155 hospital outpatient visits in Beijing from the Beijing Municipal Health Commission Information Center. We selected air pollution-sensitive diseases classified by the 10th International Classification of Diseases (ICD-10) codes^[32], including non-accidental total (A00–R99), respiratory disease (J00–J99), lower respiratory infections (J20–J22), COPD (J41–J44), and asthma (J45–J46). We built conditional Poisson regression models relating daily WHA_{air} to daily counts of cause-specific outpatient visits; daily WHA_{air} was treated as an ordinal variable. Applying the latter model, we identified the specific associations for each WHA_{air} level (2–5) relative to level 1. We hypothesized that, if the index category is appropriate, higher index levels would be associated with a greater risk of disease. Next, we developed WHA_{air} with five levels and showed its distribution from 2013 to 2018, along with AQI and AQHI.

Prediction Model for Respiratory Disease Outpatient Visits Using WHA_{air}

Long Short-term Memory Model LSTM models—a type of Recurrent Neural Network (RNN)—can handle both short- and long-term dependencies, which is crucial for improving prediction performance^[33]. In this study, LSTM was employed as the prediction model^[34]. The robustness of the model was evaluated by analyzing the daily city-level outpatient visits alongside WHA_{air} features, with particular focus on spatiotemporal properties. In our primary model, the dependent variable was the number of outpatient visits on the current day. The independent variables comprised lagged terms for outpatient visits on the previous 1–3 days, as well as the atmospheric factors, including the WHA_{air} index, and weather variables, such as average temperature and relative humidity over the same lag period. This

configuration effectively captured the lagged effects of all key predictors within the 1–3 day window^[33]. Specifically, the LSTM model comprised an LSTM layer with three time-steps, tanh activation, and sigmoid gating to capture temporal dependencies, followed by a 0.1 dropout layer for regularization and a fully connected layer for regression, trained using the Adam optimizer with MSE loss (Details in Supplementary Method S3).

Data Processing and Model Training The Beijing dataset from 2016 to 2019 showed that daily count of outpatient visits for respiratory diseases ranged from 46 to 7,244, with a mean of 837, indicating a right-skewed distribution. The dataset was split into three parts: training, validation, and test. Initially, 20% of the data were used for testing, while the remaining 80% were set aside for the combined training and validation sets. During model implementation, the training and validation sets were further split using 10-fold cross-validation. To ensure a thorough evaluation of the model's predictive ability under various conditions, the data were randomly divided into training, validation, and test sets. The Chongqing and Tianjin datasets were processed using the same method.

The performance of a trained model was assessed by its predictability on a test set. For this purpose, the Root Mean Square Error (RMSE) was applied to quantify the prediction error of the model. It measured the square root of the average squared difference between observed and predicted values. The coefficient of determination (R^2) was employed to gauge the level of model fitting and its explanatory power^[35].

Sensitivity and Robustness Analysis To assess the robustness of the model's predictive performance, we performed a time-based split sensitivity analysis. The first 80% of chronological data were used for training and the remaining 20% for independent testing. Model performance was evaluated using the R^2 and RMSE, and time-split results were compared with those from the original 10-fold cross-validation to verify prospective generalizability.

To validate the significance of WHA_{air} in predicting respiratory disease risk, we compared the performance of models with different settings. We evaluated four LSTM models: 1) the main model with all features, including WHA_{air} , ambient temperature, relative humidity, and the daily outpatient visits; 2) the main model without WHA_{air} ; 3) the main model excluding outpatient visits from the previous 1–3 days; 4) the main model without meteorological factors. The percentage change in RMSE and R^2

served as our evaluation metrics.

To verify the superiority of the WHA_{air} -LSTM framework, we conducted a standardized comparison with the Generalized Additive Model (GAM) and the ARIMA. All models were trained and tested using the same 8:2 time series data split, and their predictive performance was evaluated using R^2 and RMSE to confirm the advantages of our framework over traditional models.

To evaluate model performance during peak visit periods, we analyzed observations with daily visits above the 90th percentile and calculated the RMSE and mean absolute error (MAE).

External Validation of the Methodology

To evaluate the capability of the WHA_{air} -LSTM framework (Supplementary Figure S1) to predict outpatient visits for respiratory diseases, we validated the model by applying the same strategy and creating a city-specific WHA_{air} based on local surveillance data, along with an LSTM model trained on independent datasets from Tianjin and Chongqing. Tianjin—located near Beijing and experiencing similar air pollution patterns—contrasts with Chongqing in South China, which has a different type of air pollution, primarily ozone-related^[36,37].

RESULTS

Construction and Validation of the WHA_{air} -LSTM Framework

The health outcome datasets utilized to develop and validate the WHA_{air} -LSTM framework included three megacities: Beijing, Tianjin, and Chongqing (Table 1). For Beijing, a dataset of 12,951,191 hospital admissions was applied to develop the WHA_{air} index, while 69,963,155 outpatient visits contributed to model building and validation (Supplementary Table S1).

The Establishment and Validation of WHA_{air}

We developed the five-level index (WHA_{air}), adjusted for local air pollution excess risk, and considering both general and vulnerable populations. It links to disease risk and aligns with the national AQI through sensitivity analysis to prevent misleading results (Supplementary Method S2). Supplementary Figure S2 illustrates the lag patterns of the acute health effects of five air pollutants. We selected the largest estimate for each pollutant (Table 2). Sensitivity analysis of the exposure–response relationships between the five

air pollutants and total hospital admissions, using two different models, produced statistically significant results (Supplementary Table S2). Using these parameters, WHA_{air} for each day can be classified on a scale from 1 (lowest level) to 5 (highest level) (Supplementary Table S3). Supplementary Table S4 presented the descriptive statistics of daily WHA_{air} and AQI in Beijing from

2016 to 2018. Specifically, 2.5%, 37.9%, 34.0%, 15.9%, and 8.7% of days fell into low (1), median (2), high (3), very high (4), and severe categories (5), respectively. The distribution of WHA_{air} better aligned with that of AQI than AQHI. As Supplementary Table S3 presents, there were 9.0% of days at AQI level 5, but none at AQHI level 5.

The validation results demonstrated the

Table 1. Summary of health outcomes in this study

City	Study period	Health outcomes	Diseases	Count	Mean of daily count	Max of daily count
Beijing	2013–2018	Hospital admissions	Total	12,951,191	369	3,533
		Hospital outpatient visits	Total	69,963,155	4,049	27,648
	2016–2018	Hospital outpatient visits	RSD	13,161,528	837	7,244
			LRES	777,379	45	384
			COPD	573,957	29	431
			Asthma	420,563	23	199
Tianjin	2013–2019	Hospital admissions	Total	2,495,476	119	596
		Hospital outpatient visits	Total	29,228,691	1,112	13,407
		Hospital outpatient visits	RSD	2,805,704	106	1,419
Chongqing	2013–2019	Hospital admissions	Total	11,343,229	437	12,983
		Hospital outpatient visits	Total	124,546,360	1,690	12,373
	2018–2023	Hospital outpatient visits	RSD	18,616,021	252	3,268

Note. Total: non-accidental visits; RSD: respiratory system disease; LRES: lower respiratory system disease; COPD: chronic obstructive pulmonary disease.

Table 2. Exposure-response relationships for non-accidental hospital admissions in the whole population and the vulnerable groups associated with each $10 \mu\text{g}/\text{m}^3$ increase in daily concentrations of the five air pollutants

City	Air pollutants	All population	Aged 65 and older	Aged 15 and below
Beijing	NO_2	0.00152	0.00168	0.00101
	O_3	0.00065	0.00083	0.00058
	SO_2	0.00046	0.00042	0.00072
	PM_{10}	0.00019	0.00023	0.00015
	$\text{PM}_{2.5}$	0.00030	0.00037	0.00022
Tianjin	NO_2	0.00071	0.00102	0.00050
	O_3	0.00020	0.00014	0.00016
	SO_2	0.00001	0.00004	0.00009
	PM_{10}	0.00019	0.00019	0.00005
	$\text{PM}_{2.5}$	0.00037	0.00040	0.00010
Chongqing	NO_2	0.00139	0.00187	0.00152
	O_3	0.00077	0.00039	0.00023
	SO_2	0.00221	0.00320	0.00280
	PM_{10}	0.00022	0.00025	0.00037
	$\text{PM}_{2.5}$	0.00014	0.00017	0.00034

sensitivity of WHA_{air} in indicating the risk of respiratory diseases associated with air pollution. First, WHA_{air} as a whole was significantly associated with hospital admissions for non-accidental and respiratory diseases in the general population and vulnerable subpopulations, with stronger associations observed in the cold season than in the warm season across all groups (Figure 1). For children, WHA_{air} showed a stronger association with respiratory outpatient visits during the warm season than the cold season. Second, there was a rising trend in the associations between cause-specific hospital outpatient visits and each category of WHA_{air} (Figure 2). Compared to the reference (i.e., level 1), other WHA_{air} categories (i.e., levels 2 to 5) were significantly associated with an increasing number of hospital outpatient visits, especially for respiratory diseases and their subtypes in vulnerable

groups. For example, the relative risks for hospital outpatient visits related to respiratory diseases from WHA_{air} levels 2 to 5 were -0.1% (95% *CI*: -3.8% to 3.8%), 4.6% (95% *CI*: 0.6% to 8.7%), 8.5% (95% *CI*: 4.3% to 12.9%), and 10.9% (95% *CI*: 6.4% to 15.5%), respectively. Comparative analysis showed WHA_{air} outperformed traditional indices in health risk stratification for vulnerable populations (Supplementary Figure S3). For the non-accidental total morbidity risk, at the highest warning level, the relative risk (*RR*) of WHA_{air} was 1.09 in the population aged 15 years or younger, and 1.09 in the population aged 65 years and older. In comparison, the corresponding *RR* values of AQI were 1.04 and 0.99, and those of AQHI were 1.08 and 1.00, respectively. Using the same approach, we developed the WHA_{air} index for the cities of Tianjin and Chongqing (Supplementary Table S5) and

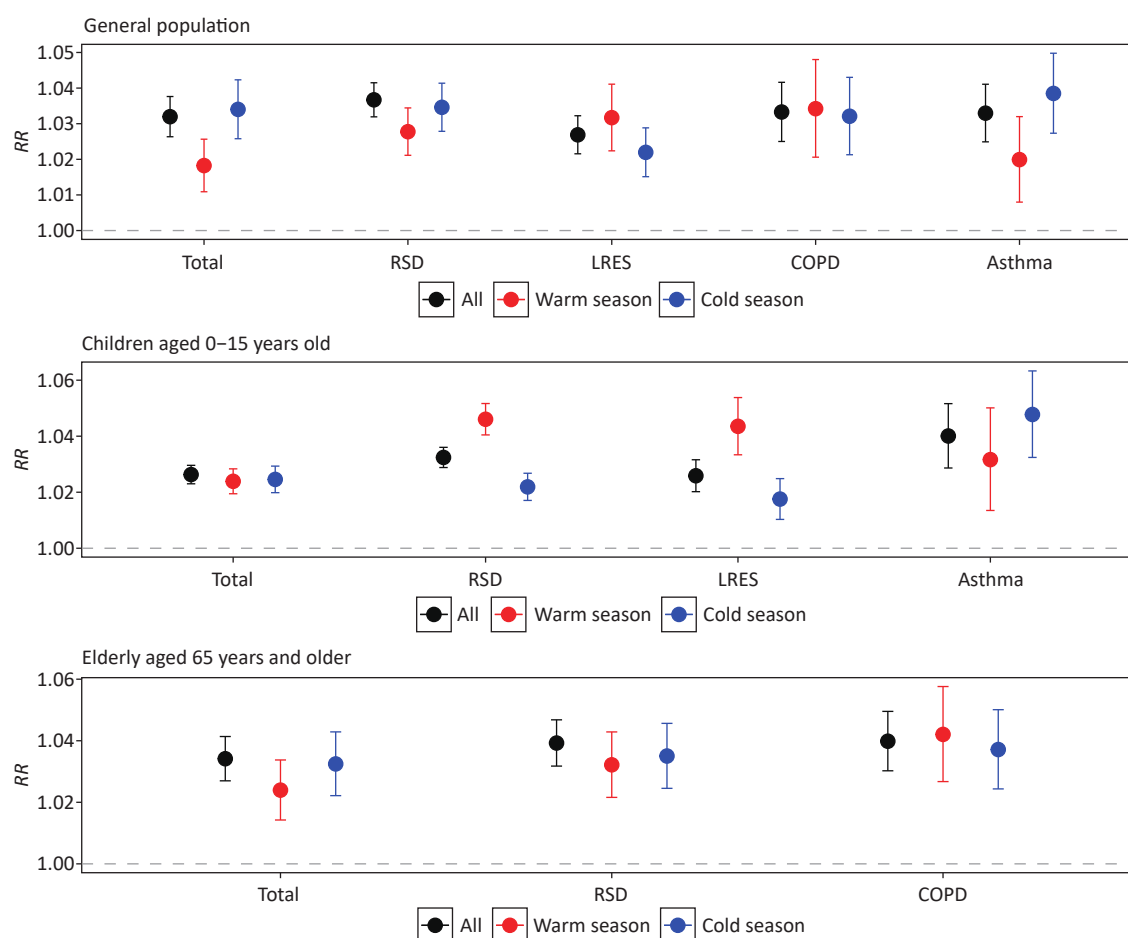


Figure 1. Associations between WHA_{air} and outpatient visits for respiratory diseases across various population groups and seasons in Beijing, 2013–2018. Total: non-accidental hospital outpatient visits; RSD: respiratory system disease; LRES: lower respiratory system disease; COPD: chronic obstructive pulmonary disease; WHA_{air} : the Warning for Health Risk of Atmospheric Environment.

validated each city's index using local hospital outpatient data, including 29,228,691 visits in Tianjin and 124,546,360 visits in Chongqing. The external validation results shown in Supplementary Figures S4 and S5 also indicated that the WHA_{air} index outperformed AQI in predicting city-level respiratory outpatient visits.

Predictive Performance and Robustness of the WHA_{air} -LSTM Framework

Our main model results showed that the R^2 for the respiratory disease prediction model with WHA_{air} is 0.963, RMSE is 53.5 visits, and it indicated

significant robustness (Figure 3A). The optimal model structure was determined through extensive validation (Supplementary Figure S6). During peak periods (above the 90th percentile of visit volume, i.e., 1,322.4 visits), the main model achieved an RMSE of 540.46 visits and an MAE of 243.2 visits; among the 302 test samples above this threshold, it predicted 233 above it, yielding a detection rate of 77.15% (Supplementary Figure S7). We compared four predictive models to examine how different input variables and model complexity affect predictive accuracy (Figure 3). The R^2 and RMSE values for these models are as follows: Model A (full

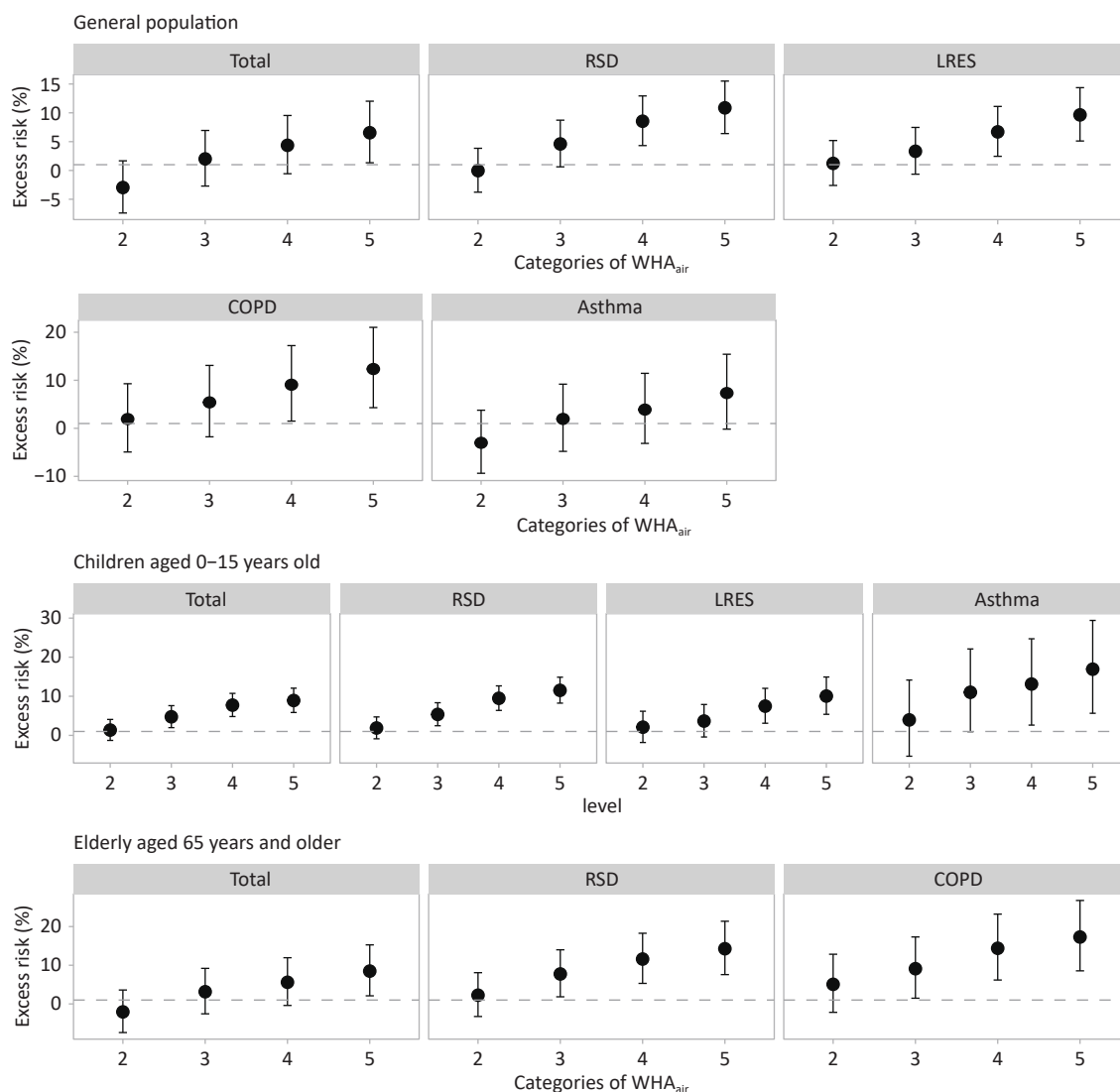


Figure 2. Associations between each category of WHA_{air} and outpatient visits for respiratory disease in the entire population and vulnerable groups. Total: non-accidental hospital outpatient visits; RSD: respiratory system disease; LRES: lower respiratory system disease; COPD: chronic obstructive pulmonary disease; WHA_{air} : the Warning for Health Risk of Atmospheric Environment.

model): 0.963 and 53.5; Model B (excluding WHA_{air}): 0.904 and 82.2; Model C (excluding previous-day hospital visit): 0.078 and 328.6; and Model D (excluding temperature and relative humidity): 0.932 and 65.1. The comparisons indicate that relying solely on WHA_{air} and meteorological factors (Models A and C) results in poorer prediction of respiratory risk. Excluding WHA_{air} (Model B vs. A) lowered accuracy and stability ($\Delta\text{RMSE} = +44.1\%$, $\Delta R^2 = -2.7\%$), while removing temperature/humidity had minimal impact. These findings underscore the significance of WHA_{air} in capturing fluctuations in hospital outpatient visits compared to the general trend.

Sensitivity analyses demonstrated the robustness of the model (Supplementary Figure S8). Under the time-based split, the independent test set performance was slightly lower than that under random splitting (for the Beijing dataset, R^2 decreased from 0.963 to 0.891). Despite this performance drop, the model still captured the overall trend in daily outpatient visits during the independent test period (Supplementary Figure S7). Furthermore, compared with traditional statistical models, the WHA_{air}-LSTM framework

demonstrated superior predictive performance. On the same validation dataset, the LSTM model significantly outperforms the generalized additive model and the seasonal ARIMA model (Supplementary Table S6).

Generalizability across Megacities

The framework's universality was confirmed through external validation in two major cities, Tianjin and Chongqing, each with unique air pollution patterns and population traits (Supplementary Table S5). The performance of the models using data from these cities was similar to that of Beijing. The WHA_{air} model exceeded the AQI in predicting respiratory outpatient risks, as illustrated in Supplementary Figures S4 and S5. The LSTM model with 128 units showed consistent, strong predictive results on the test data from both cities (Supplementary Figures S9 and S10). Specifically, the R^2 for Tianjin's test set was 0.905 with an RMSE of 40 visits, while Chongqing's R^2 was 0.899 with an RMSE of 80 visits. The effectiveness of WHA_{air} was further confirmed with additional data from Tianjin and Chongqing. The model validation for the two cities also employed a strict time-

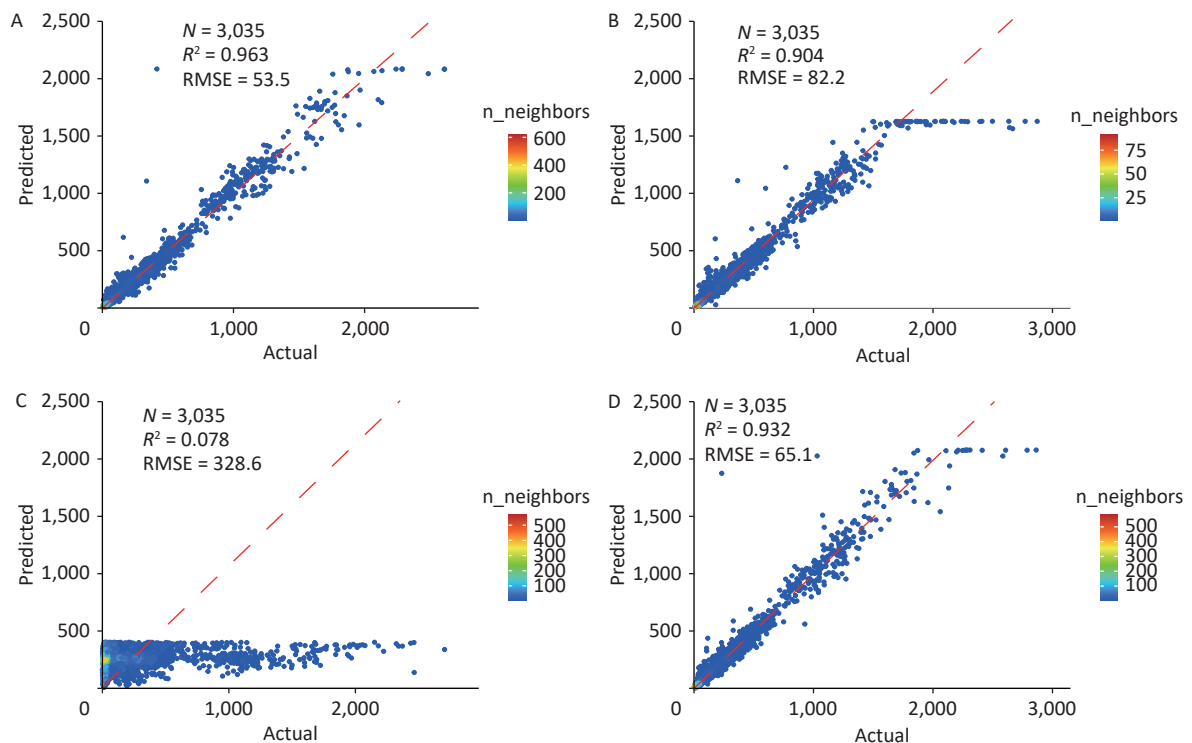


Figure 3. Scatterplot of actual versus predicted outpatient visits for model comparison. (A) Full model. (B) WHA_{air}-excluded model. (C) Outpatient-visits-excluded model. (D) Temp-Humidity-excluded model. WHA_{air}: the Warning for Health Risk of Atmospheric Environment; RMSE: the Root Mean Square Error.

segmented design. Detailed prediction results are provided in Supplementary Figures S11 and S12.

DISCUSSION

Based on over 223.7 million hospital visits from three megacities, the city-specific WHA_{air}-LSTM framework developed and validated in this study demonstrated its predictive ability for respiratory outpatient visits. Notably, our framework offered four major innovations over existing research: 1) we built the model focusing on individual cities rather than the entire country; 2) when selecting model features, we created the WHA_{air} index to represent the overall impact of combined air pollution instead of individual pollutants; 3) we established an effective model by inputting four variables for prediction; 4) we performed strict external validation using datasets from Tianjin and Chongqing, which confirmed its universality. Therefore, the WHA_{air}-LSTM framework may serve as an effective tool for integrating environmental monitoring, disease prevention, and healthcare, thereby contributing to city-level early warning systems for disease risk.

Our framework provides an effective method for predicting respiratory disease risk, with several key benefits. First, integrating the WHA_{air} index with the LSTM model overcomes traditional limitations. Unlike models that rely on single pollutants, WHA_{air} combines the effects of multiple pollutants, enabling the model to better identify non-linear relationships between air pollution and respiratory disease^[38]. Second, including outpatient data from the past three days enhanced predictive stability and relevance. It captured short-term visit trends and emphasizes pollution-driven extra visits, aligning with the 1–3-day lag of respiratory diseases. Third, the framework balances accuracy and usability. It delivers actionable performance with only four readily available variables within a three-day exposure window. Notably, prediction errors of the WHA_{air}-LSTM framework increase when hospital visits exceed the 90th percentile, primarily because of unpredictable extreme peaks from complex social behaviors^[39,40]. Nevertheless, from a public-health perspective, its ability to capture the acute effect and upward slope of surges provided hospitals with sufficient lead time to initiate emergency plans. To evaluate prospective predictive performance, we performed a time-based sensitivity analysis in addition to random split evaluation. The model achieved satisfactory accuracy and captured surging trends in future outpatient visits ($R^2 = 0.891$). As it

does not rely on future information during training, the LSTM model showed favorable generalizability for real-world public health applications.

The WHA_{air}-LSTM framework showed strong external validity and global potential. Many models that connect air pollution to health risks, built on traditional regression or simpler machine learning methods, often lack thorough external validation, limiting their usefulness. Although these models perform well in primary cities, they tend to have higher mean absolute error (MAE) in nearby regions^[41]. Models trained across multiple centers often encounter performance gaps during extrapolation because of data heterogeneity^[42]. In contrast, our framework has undergone thorough external validation in Tianjin and Chongqing: two cities with different pollution patterns^[36]. Air pollution in Tianjin is mainly caused by industrial emissions, while Chongqing's pollution is primarily affected by its mountainous terrain and basin-like geography^[37]. These scenarios align with global paradigms such as the U.S. Rust Belt, Western European industrial cities mirroring Tianjin, and subtropical Brazilian and Indian cities resembling Chongqing. Such external validation enhances the model's applicability in urban air health risk assessment. It is noteworthy that the WHA_{air} index needs to be customized based on local historical data, so that the model can adapt to the unique urban pollution patterns.

Using the city-specific WHA_{air}-LSTM framework to predict the risk of air pollution-related diseases provides a valuable tool for public health and medical services. On one hand, health professionals from the Centers for Disease Control and Prevention, hospitals, clinics, and community medical organizations can take different actions based on the level of WHA_{air} and deliver timely, authoritative information to the public, including the general population and vulnerable groups. On the other hand, this approach can be integrated into the development of early warning systems—a cost-effective risk-reduction measure adopted worldwide^[43]. Therefore, by being informed of potential outpatient visits in advance, medical services can prepare for the increased demand caused by heavy pollution, such as appropriately relocating medical resources. Doctors can also advise patients to monitor their health and avoid exposure to hazardous conditions and pollution.

However, three limitations must be acknowledged. First, data limitations restrict WHA_{air} to city- or county-level analyses, precluding

assessment of intra-urban variability, and the model showed limited predictive performance for non-respiratory diseases. Second, shifts in healthcare benchmarks and weekend or holiday effects may bias temporal coverage, and the model's fixed parameters may fail to capture sudden surges in visits driven by these factors. Third, our simplified model does not account for potential confounders such as extreme weather events or seasonal co-epidemics of infectious diseases, which may contribute to prediction discrepancies during extreme peak periods^[44]. Future research could explore disease-specific indices and their application in city-level prediction.

CONCLUSIONS

This study developed and validated a city-specific predictive framework (WHA_{air}-LSTM) that effectively forecasts respiratory outpatient visits by integrating multi-source environmental and health data. This framework can be applied as a specific tool to facilitate early warning of respiratory disease risks.

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Authors' Contributions Data curation, Formal analysis, Writing-original draft: Wenxuan Zhao, Yu Wang; Resources, Investigation: Changzhen Xiang, Chenfeng Li, Chen Chen, Jiaonan Wang, Jianlong Fang, Feng Lu; Formal analysis, Methodology, Writing-original draft: Kai Chen, Shilu Tong; Conceptualization, Methodology, Project administration, Writing-review & editing: Jie Ban, Xiaoming Shi; All authors critically revised the manuscript and approved the final version for publication.

Data Sharing Data on air pollution concentrations can be obtained from the National Monitoring Platform (<https://air.cnemc.cn:18007>). The total number of daily hospitalizations is sourced from the Municipal Health Commission Information Center. The data that support the findings of this study are available from the corresponding author upon reasonable request. The supplementary materials will be available in www.besjournal.com.

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