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Air Pollution-Related Mortality in Bangkok: A Time-Series Neural Network Analysis

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Abstract:

Objective: This study aimed to predict and analyze air pollution-related mortality rates in Bangkok, Thailand, using a comprehensive neural network (NN) model. Objectives included analyzing temporal dynamics, evaluating model effectiveness, and identifying the influential factors.

Material and Methods: Daily air quality and mortality data from 2016 to 2020 were used. We employed recurrent neural networks (RNNs), long short-term memory (LSTM), and gated recurrent units (GRU) models to capture the complex relationships between six key pollutants and mortality. The best model was selected based on the lowest R^2 and mean difference from the Bland–Altman analysis. SHAP feature importance and subgroup analyses for age (0–5, 5–60, and 60+ years) and cause of death (respiratory, circulatory, and other) were conducted.

Results: Analysis included 170,612 mortality cases over 1,828 days, with a median=36 daily premature deaths. An LSTM model with a 23-day time lag demonstrated the highest predictive accuracy for overall mortality. Subgroup analysis

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identified different optimal models; an RNN model was best for the “Older Adult” subgroup, and an LSTM model was best for the “Respiratory” subgroup. For feature importance, relative humidity, particulate Matter ($PM_{2.5}$), and ozone (O_3) were the most influential for overall mortality. The most influential factors for older adults were PM_{10}, $PM_{2.5}$, and carbon monoxide (CO); for respiratory, $PM_{2.5}$, nitrogen dioxide (NO_2), and PM_{10} were the most influential.

Conclusion: This study demonstrates NN's potential in predicting air pollution-related mortality rates in Bangkok. Findings highlight the importance of considering temporal dynamics, subgroup-specific characteristics, and the key environmental factors in model development. These data-driven insights can inform public health policies and facilitate targeted interventions to mitigate the health impacts of urban air pollution.

Keywords: air pollution, machine learning, recurrent neural network, time series prediction

Introduction

Air pollution is a significant global health threat, 90% of the population in risky air quality areas is exposed to cardiovascular and respiratory diseases, resulting in millions of premature deaths yearly[1]. In vulnerable populations, pregnant women and children are exposed to adverse preterm births and increased pediatric asthma by particulate matter (PM) and pollutants, such as $PM_{2.5}$ and nitrogen dioxide (NO_2)[2]. Outdoor air pollution is a significant health problem that impacts people around the globe, leading to around 4.2 million premature deaths in 2019 from fine particles related to heart and lung diseases as well as cancer. The World Health Organization (WHO) reports that 68% of the population died from ischemic heart disease and stroke, with 14% each from chronic obstructive pulmonary disease and acute lower respiratory infections, and 4% from lung cancer. Low- and middle-income nations were hit the hardest, accounting for 89% of these fatalities, especially in the WHO South-East Asia and Western Pacific Regions, emphasizing the severe effects of air pollution on health[3].

Bangkok, the capital of Thailand, is experiencing rapid urban growth, resulting in poor air quality due to emissions from cars, factories, and farming fires, all of which raise PM levels[4]. The PM_{10} levels exceed the WHO recommended levels, causing respiratory problems and hospital admissions[5], while $NO_{2,}$ with high-intensity ultraviolet radiation, develops the secondary air pollution ozone[6]. This complex relationship highlights the need for comprehensive strategies to address air pollution and protect public health in tropical, densely populated cities. $PM_{2.5}$ levels in Bangkok rise in the winter (November to February) from agricultural burning in the northeast, especially in sugarcane fields[7], and traffic emissions from heavy-duty vehicles, especially near expressways[8]. Winds from the northeast frequently carry pollutants to Bangkok[9].

Leveraging machine learning (ML) in air quality management can enhance our understanding of pollution trends and their health impacts, particularly when predicting mortality rates related to air pollution. The ability of ML to analyze complex datasets helps uncover nonlinear relationships among various factors, such as emissions, weather conditions, and urban development.

Deep learning techniques can be used to obtain detailed satellite data for pollutants such as $PM_{2.5}$, enabling accurate calculations of exposure and related mortality rates. This method has been used in the Yangtze River Delta to evaluate premature deaths owing to $PM_{2.5}$ exposure, and notable regional differences were found[10].

Gradient-boosted trees and neural networks can effectively capture complex relationships between air pollutants and weather conditions. These models tend to be more efficient and accurate than standard chemical transport models, as shown by studies on NO_2 and O_3 levels in Germany[11].

The distributed lag nonlinear model has been used to predict respiratory disease deaths[12], and it was found that the risk increased with prolonged exposure to low temperatures and high $PM_{2.5}$ levels, with significant cumulative lag effects at 3 and 5 days, respectively, demonstrating the superior performance of the model in early warning. These models use environmental and weather data to estimate respiratory disease deaths, offer early alerts, and allow prompt action[12].

Neural networks have been employed to effectively predict daily mortality rates by incorporating features such as NO_2 concentrations, temperature, and socioeconomic factors. In a study based on the Greater London area, neural networks outperformed linear models. Long short-term memory (LSTM) networks have been utilized to consider temporal dependencies, enabling the examination of time-lagged effects on mortality rates and reducing the mean squared error by 73%[13].

The objective of this study is to predict mortality rates in Bangkok by developing a comprehensive neural network model that utilizes air pollution data through time-series analysis. This study aimed to analyze the temporal dynamics between air pollution and mortality, evaluate the effectiveness of predictive models, and discuss the outcomes of the model using feature importance. Specifically, this study examined how air pollution affects all-cause and cardiopulmonary mortality rates in different age groups. Compared with previous studies, the present analysis applied deep learning models to ensure the highest predictive accuracy when considering complex time-series air pollution and mortality data. In addition, the importance of features was analyzed to assess the most influential factors related to mortality, thereby enhancing our understanding of the factors affecting mortality trends.

Material and Methods

Data sources

The analyses in this study included key pollutants related to human health. Pollutants included PM_{10}, $PM_{2.5}$, carbon monoxide, sulfur dioxide, nitrogen dioxide, and ozone. These pollutants were assessed along with various atmospheric factors, such as wind speed, temperature, and relative humidity. Air data were retrieved from the Thai Pollution Control Department (PCD). The method used to measure the pollutants conformed to the US EPA standards. The hourly air quality data between January 1, 2016 and December 31, 2020 were retrieved from the PCD website via an application programming interface. The dataset used in this study was collected by the PCD using hourly air quality measurements performed at twelve strategically located monitoring stations spread across Bangkok.

The mortality data were obtained from the Strategic and Planning Division of the Ministry of Public Health. The mortality dataset included a detailed classification of the causes of mortality in Thai free-text format for each fatality. Deaths caused by accidents and unnatural causes were excluded from the analysis to focus on the health air pollution-related fatalities.

Data preprocessing

We utilized a robust imputation method based on the random forest algorithm developed in R to address the missing data and normalized the data using the Min-Max Scaler to ensure comparability and accuracy. Finally, we extracted time-series data from our dataset using a systematic approach, starting at a specified date and extending up to a predetermined endpoint that is defined by a specific time frame, enabling us to examine the relationship between air quality exposure and health outcomes over an extended period.

Neural network models

This study employed various neural network structures, including simple recurrent neural networks (RNNs), LSTM, and gated recurrent units (GRU). Each model features an input layer designed to handle time-series data, with the size adjusted to fit the specific time lag and feature count of the dataset. A hidden neural network layer comprising units matching the length of the time lag was used to capture patterns in the sequential data. The output layer comprises a single unit with a rectified linear unit activation function, which enables continuous predictions that represent the predicted results of the time-series data.

Experimental design

This study employed a two-part approach for model development, utilizing a training dataset between 2016 and 2018 and a testing dataset between 2019 and 2020. The primary objective was to identify the optimal model configurations to predict premature fatalities based on varying input time lags (1–30, 90, 180, and 360 days). A sliding window method was employed to evaluate the performance of the models as they were adjusted to different input sequences. The predictive accuracy of each model was assessed using multiple metrics to identify the best combination of input time lag and prediction horizon.

Model evaluation

Predictive models were developed with hyperparameter tuning, and their performance was evaluated using a Bland–Altman analysis to compare the predicted and actual values. The best model was selected based on two key criteria from the Bland-Altman plot. First, a linear regression was performed on the plot's differences versus means to quantify proportional bias. The model with the lowest R-Squared (R^2) from the linear regression on the Bland-Altman plot was preferred, as this indicated that the model's prediction errors were not linearly dependent on the magnitude of the measured values. This selection assumes that the lowest R^2 value signifies that the residuals (the differences between predicted and actual values) are randomly scattered around the mean difference and are not linearly (systematically) related to the magnitude of the measurements. Therefore, a low R^2 suggests that the model's predictive accuracy is consistent across the entire range of values, indicating homoscedasticity and a lack of proportional bias. Second, the model with a mean difference closest to zero was chosen to ensure minimal overall systematic bias.

Subgroup analysis

We categorized fatalities into three age groups: young (0–5 years), adult (5–60 years), and older adult (60+ years). Using the Llama 3.2 model with prompt engineering based on the International Classification of Diseases, Tenth Revision (ICD-10) manual, we systematically organized causes of death in the Thai language into circulatory diseases, respiratory diseases, and other conditions. The accuracy of the cause of death categorization was measured by comparing the groups classified by LLM with the groups independently, manually classified by an internal medicine specialist. The Kappa statistic was used to evaluate the agreement between the Llama 3.2 model's classifications and those made by the specialist.

Features important analysis

This study used SHapley Additive exPlanations (SHAP) to analyze feature importance, visualize absolute SHAP values by time and feature, and identify the most influential features by summing the mean SHAP values across all subgroups and testing the datasets.

Results

Populations

The dataset spans 1,828 days across five consecutive years and includes the mortality statistics in Bangkok. It includes daily premature death counts and subgroup-specific data according to age (young, adult, and older adults) and cause of death (respiratory, circulatory, and other diseases), with a population of 100,000 individuals used as the denominator for the mortality rate per 100,000 individuals. The total number of mortalities was 170,612 cases; the average annual death rate was 34,122.4 cases per year.

Figure 1 shows a data flow diagram of a subgroup with the number of cases, broken down by age and cause of death. A sample of 300 cases was used for evaluation with an expert to measure the level of agreement of the automated ICD-10 assignment with Llama 3.2.

Table 1 shows a summary of the death statistics for each subgroup. Figure S1 (in Supplementary Information [SI]) presents a time-series plot of premature death rates and $PM_{2.5}$ concentrations in Bangkok between 2016 and 2020; training (blue) and testing (orange) periods were evaluated for model performance. The y-axis represents the premature death rates per 100,000 people and $PM_{2.5}$ concentrations in μg/m^3, while the x-axis represents dates.

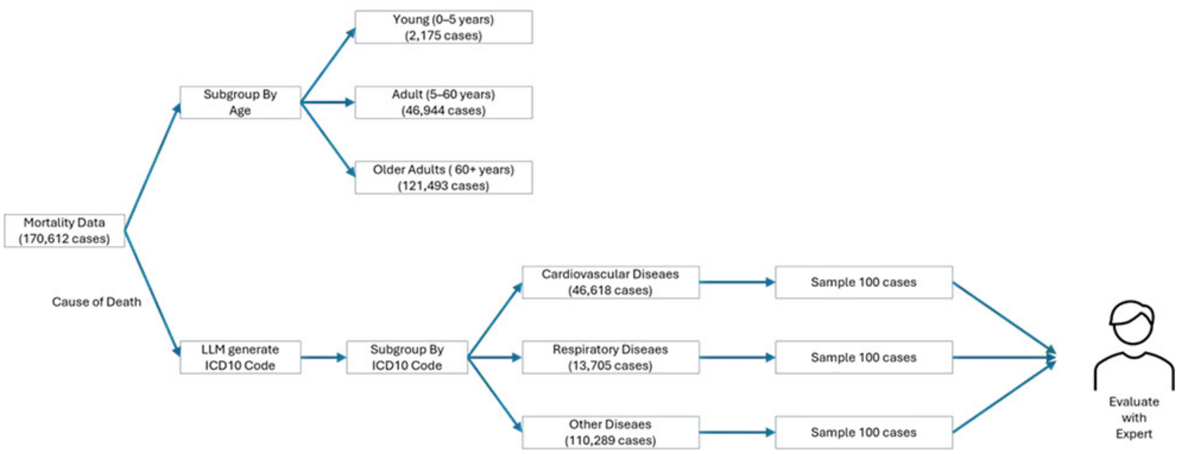


Figure 1 Data flow diagram

Table 1 Death statistics of each subgroup

	Median	Min	Q1	Q3	Max
Populations	5,676,648	5,527,994	5,666,264	5,682,415	5,686,646
Counts	1,828	1,828	1,828	1,828	1,828
Subgroup (daily death)					
Overall					
Premature	36	18	32	41	66
Age					
Young	1	0	0	2	8
Adult	23	10	20	26	42
Older adult	34	13	30	38	61
Cause of Death					
Respiratory	4	0	3	5	12
Circulatory	18	6	15	21	37
Others	36	17	32	40	61

The gray bands highlight long holiday periods, which may impact the air quality and mortality patterns. Table S1 (SI) presents pollutant and atmospheric statistics, and Figure S2 (SI) shows the training and testing time-series plots for each feature.

Overall model performance

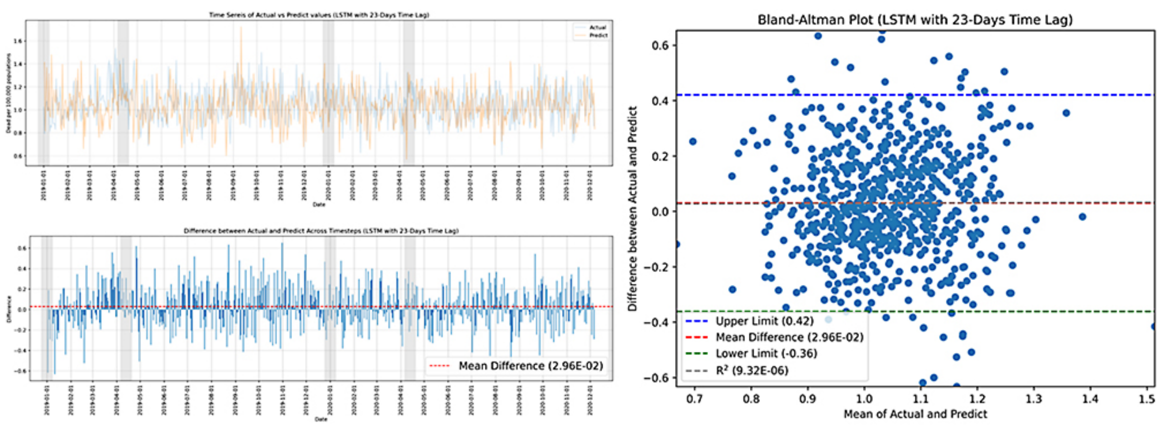
Upon completing the model development phase, the models were evaluated using two primary performance metrics: R^2 and mean difference. The results are presented in Table 2, which lists the performance metrics of the various neural network models to predict premature death rates in Bangkok. The LSTM model with a 23-day lag exhibited the lowest R^2 value of 9.32E-06 with a mean difference of 2.96E-02. Contrastingly, the GRU models with shorter time lags (18 and 17 days) exhibited better performance, with lower R^2 values and mean differences.

Temporal analysis

The model exhibits a consistent trend of underprediction following long holidays in Thailand, suggesting a potential area for further investigation. Figure 2 illustrates a time-series plot of the actual values (blue) versus the predicted values (orange) over the testing period (2019–2020). The y-axis represents deaths per 100,000 people, and the x-axis represents dates. The gray bands highlight long holidays in Thailand, specifically the New Year and Songkran. The LSTM model with a 23-day lag time showed that the predicted values closely followed the trends of the actual values. The difference plot between actual and predicted values is presented over the same time lag, with the y-axis corresponding to the difference (actual – predicted) and the x-axis corresponding to the dates. The Bland–Altman plot shows the limits of agreement of [–0.36, 0.42].

Subgroup analysis

Figure S3 (SI) shows the optimal model selection for each subgroup, highlighting the best combination of neural network architecture and time lag that resulted in the lowest R^2 value and the smallest mean difference between the actual and predicted outcomes. The findings indicate that RNN 7-days, RNN 23-days, and RNN 21-days are the most effective predictive models for the "Young," "Adult," and "Older Adult" subgroups, respectively, whereas LSTM 22-days, RNN 23-days, and LSTM 17-days correspond to "Respiratory," "Circulatory," and "Other" subgroups. Table 3 summarizes the models along with their R^2 and



LSTM=long short-term memory

Figure 2 Time series plot, difference plot, and Bland–Altman plot of LSTM with a 23-day lag mean difference values. Figure S4 (SI) shows the Bland–Altman plot for each subgroup. Figure S5 (SI) shows the comparative confusion matrix of ICD-10 cause-of-death assignments using automated Llama 3.2 generation and manual expert review. Cell values indicate the number of matched and mismatched predictions by category. Percent agreement was 83% overall in 300 cases, performing well on cardiovascular, respiratory, and other at 68%, 90%, and 91%, respectively. The model's performance varied in specific subgroups. The calculated Kappa score is 0.7450 and indicates a substantial level of agreement between the model's predictions and the true labels, after accounting for chance agreement.

Model performance varied across age and cause-of-death subgroups. The model for the "Older Adult" subgroup demonstrated predictions that closely corresponded to actual values, while the "Adult" subgroup showed a slight underprediction. Conversely, the "Young" subgroup exhibited relatively poor performance, with near-zero daily deaths and predictions. Among the cause-of-death subgroups, the "Respiratory" subgroup had the lowest mean difference, and the "Circulatory" subgroup had the lowest R^2. Additionally, a notable trend of higher actual deaths than predicted values was observed following long holidays in Thailand. The varying levels of agreement between the predicted and actual outcomes for each subgroup are visually represented in the time-series plots in Figure 3.

Feature importance analysis

Feature importance analysis showed that the factors influencing mortality differed significantly based on

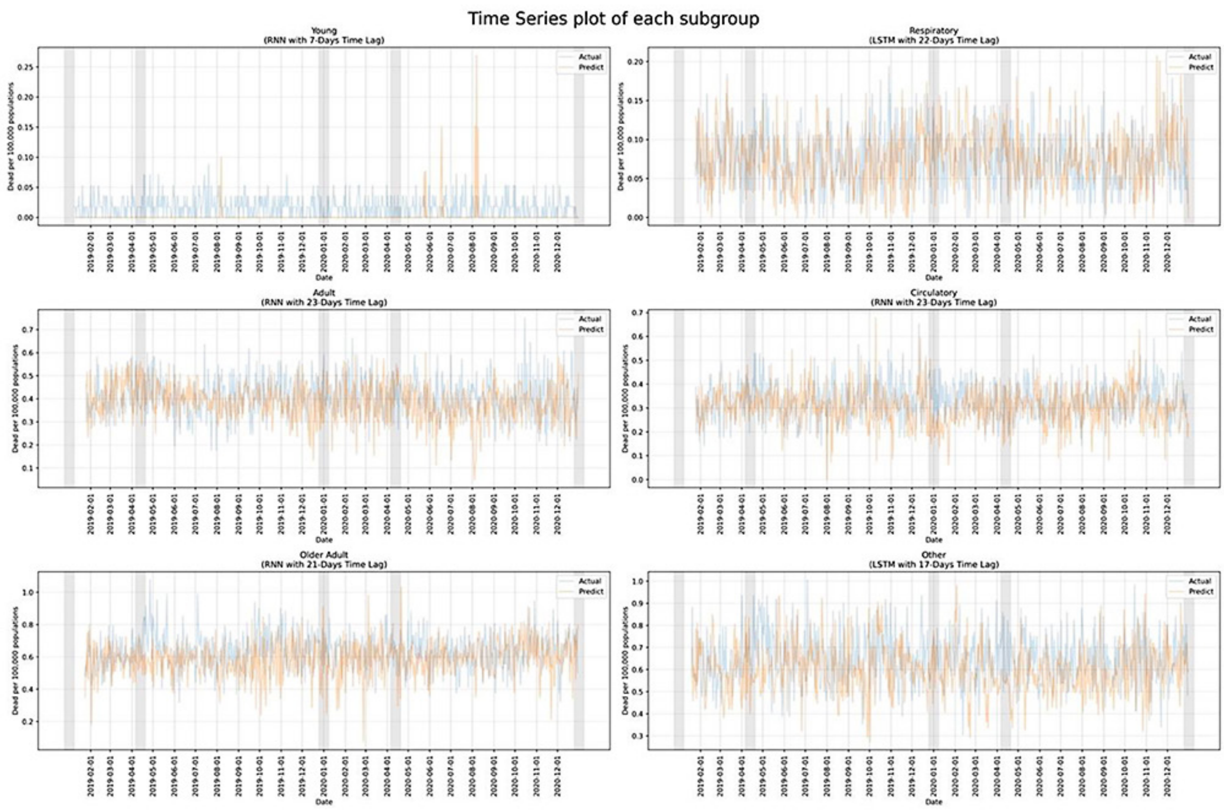


Figure 3 Time-series plot of actual vs predicted values for each subgroup

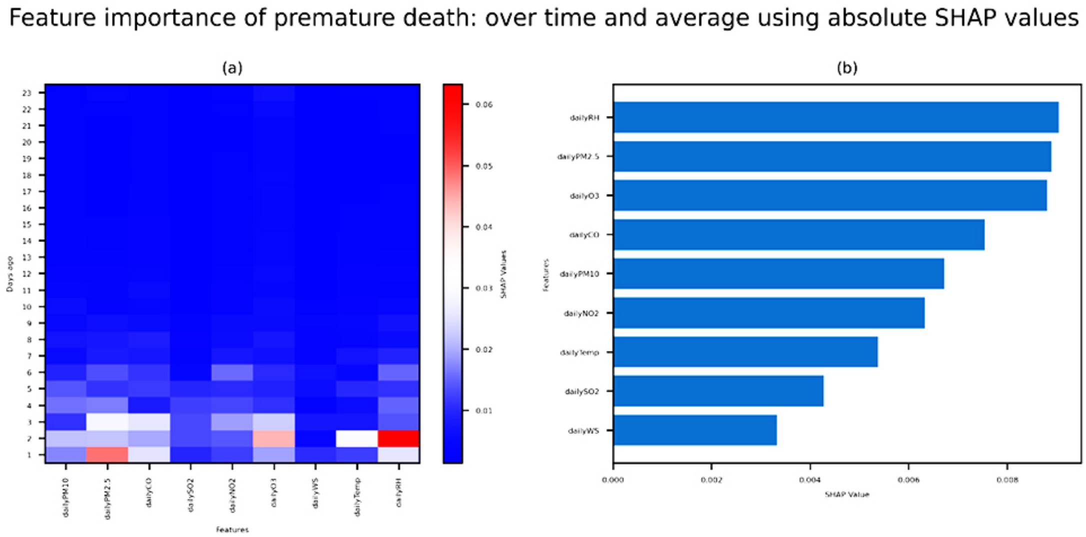


Figure 4 Feature importance of premature death: over time and average using absolute SHAP values. (a) A heatmap illustrating feature importance over time, with the color intensity representing the absolute SHAP value. The plot highlights the strong influence of daily relative humidity (dailyRH), $PM_{2.5}$, and O_3 in short time lags. (b) A bar chart showing the overall average feature importance, ranking features by their mean absolute SHAP value across the testing dataset. The plot indicates that daily relative humidity, daily $PM_{2.5}$, and daily O_3 are the most influential features for predicting mortality

timeframe, age group, and cause of death. As seen in Figure 4, daily relative humidity, $PM_{2.5}$, and O_3 were the most crucial features for predicting overall mortality over a seven-day period.

The analysis of age subgroups revealed distinct patterns (Figure S6 [SI]). The "Young" subgroup was most affected by daily relative humidity, NO_2, and PM_{10}. In contrast, the "Adult" subgroup was primarily influenced by daily PM_{10}, NO_2, and $PM_{2.5}$, with effects that could persist for up to 17 days. For the "Older Adult" subgroup, the main influential factors were daily PM_{10}, $PM_{2.5}$, and CO, with a notable impact occurring approximately four to five days after exposure.

Furthermore, the feature importance for each cause-of-death subgroup also showed unique trends (Figure S7 [SI]). For circulatory deaths, daily O_3, NO_2, and RH were the key drivers. For respiratory deaths, daily $PM_{2.5}$, NO_2, and PM_{10} were most influential, with the effects appearing within two to six days. Finally, for all other causes of death, daily PM_{10}, $PM_{2.5}$, and CO were the most critical factors, with a rapid impact felt within two to three days.

Figure 4 Feature importance of premature death: over time and average using absolute SHAP values. (a) A heatmap illustrating feature importance over time, with the color intensity representing the absolute SHAP value. The plot highlights the strong influence of daily relative humidity (dailyRH), $PM_{2.5}$, and O_3 in short time lags. (b) A bar chart showing the overall average feature importance, ranking features by their mean absolute SHAP value across the testing dataset. The plot indicates that daily relative humidity, daily $PM_{2.5}$, and daily O_3 are the most influential features for predicting mortality.

Discussion

Key findings

This study aimed to predict the mortality rates in Bangkok by developing and evaluating neural network models utilizing air pollution data by conducting a time-series analysis. Our findings indicate that the performance of the models varies significantly based on the chosen neural network architecture (RNN, LSTM, or GRU) and the time lag considered. The residual from the LSTM model with a 23-day lag exhibited the lowest R^2, indicating a potentially high predictive accuracy without systematic bias. The R^2 value used in this approach proves that the residuals, which were the differences between the predicted and actual values, were not linearly associated with average daily mortality. Thus, the lowest R^2 of the residuals identifies the model with the least linearity bias. Notably, the GRU models with shorter time lags (18 and 17 days) also demonstrated promising performance, suggesting that shorter time windows may be more effective in capturing the temporal dynamics of the impact of air pollution on mortality in Bangkok.

Analysis of the model performance across different subgroups revealed distinct patterns. The most effective predictive models varied across age subgroups ("Young," "Adult," and "Older Adult") and disease subgroups ("Respiratory," "Circulatory," and "Other"), highlighting the need for a tailored approach to mortality rate prediction. These findings underscore the importance of considering individual characteristics and disease-specific vulnerabilities when developing and applying predictive models.

Feature importance analysis identified the key environmental factors that influence mortality risk. Daily $PM_{2.5}$, PM_{10}, and NO_2 levels emerged as the most influential features across all subgroups, emphasizing the crucial role of air quality in determining mortality rates. The analysis also revealed distinct patterns of feature importance across the different subgroups. For example, the "Young" subgroup showed a strong association with daily RH, NO_2, and PM_{10}, while the "Adult" subgroup exhibited a greater influence of PM_{10}, NO_2, and $PM_{2.5}$. These findings provide valuable insights into the specific environmental factors that contribute to mortality risk within different population segments.

Error analysis

For the young subgroup, we found that 356 of 745 cases were related to congenital disorders, as seen in Table S2.

Comparison with the existing literature

Existing research has consistently demonstrated the association between air pollution and increased mortality in urban centers, including Bangkok. Studies have utilized traditional statistical methods, such as time-series analyses and generalized additive models, to establish significant correlations between PM and mortality rates[14]. Buya et al. (2025) analyzed satellite-based $PM_{2.5}$ data across Thailand from 2015 to 2019, revealing significant spatiotemporal correlations between monthly $PM_{2.5}$ levels and cardiorespiratory mortality, with stronger effects in the central and northern provinces and during the dry season, and quantifying percentage changes in mortality based on $PM_{2.5}$ concentrations.[15] Thongphunchung et al. (2022) examined the Eastern Economic Corridor (EEC) in Thailand using a case-crossover design and the conditional Poisson model, finding a significant association between ambient air pollution and outpatient department (OPD) visits and mortality from various causes. Furthermore, it was found that a 1 μg/m^3 increase in PM_{10} was associated with 0.79% increase in mortality from skin and subcutaneous tissue diseases, and a 1 μg/m^3 increase in $PM_{2.5}$ was associated with an increase in mortality to 0.79% from circulatory diseases, 0.82% from respiratory diseases, and 2.91% from skin and subcutaneous tissue diseases[16]. These studies have provided valuable insights into the acute effects of air pollution on public health. However, our study employed advanced neural network models, which offer a more sophisticated approach to capturing the complex nonlinear relationships inherent in environmental health data. This method allows for a more nuanced understanding of temporal dynamics and subgroup-specific vulnerabilities, potentially surpassing the predictive capabilities of traditional models.

Furthermore, while previous research has largely focused on the impact of specific pollutants such as PM_{10} and $PM_{2.5}$, this study integrates a broader range of environmental factors, aiming to provide a more holistic understanding of the influence of air pollution. In comparison to studies that focused on linear models, the neural network models used in this study enable the modelling of more complex interactions between the environmental factors and mortality rates. Moreover, while most studies have looked at general mortality, this study incorporates subgroup-specific characteristics. This is important because previous studies have shown that the impact of air pollution is not equal across all demographics[13]. Thus, this study contributes to the growing body of literature that emphasizes the importance of considering the social determinants of health in environmental risk assessments.

Implications and suggestions for future research

This study demonstrated the potential of using neural network models to predict air pollution-related mortalities in Bangkok by leveraging air pollution data. The findings highlight the importance of considering temporal dynamics, subgroup-specific characteristics, and the influence of key environmental factors when developing effective predictive models. These insights have considerable implications for public health policy-making, enabling targeted interventions to mitigate the impact of air pollution on public health and improving the overall health outcomes of the population in Bangkok. The machine learning models can quantify the interactive longitudinal impact of air pollutants. This suggests that to accurately address the health risk of air pollution, the pollution index should be a composite index calculated from machine learning. Furthermore, our subgroup analysis highlights the particular vulnerability of older adults. A comprehensive early-warning system should be based on a combination of air pollutants, temperature, relative humidity (RH), and age to accurately predict and prevent adverse health outcomes.

Future research should investigate the impact of confounding factors on mortality rates and explore the generalizability of these findings to other urban environments. Additionally, incorporating real-time air quality data and integrating advanced ML techniques, such as ensemble methods and deep learning architectures, can further enhance the accuracy and robustness of mortality rate prediction models.

Strengths and limitations of the study

The strength of this study lies in its comprehensive approach to predicting mortality rates in Bangkok by developing and evaluating neural network models tailored for time-series air pollution data. By systematically comparing architectures—RNN, LSTM, and GRU—across different time lags, the study identifies the LSTM model with a 23-day lag as the most accurate predictor, while also highlighting the effectiveness of GRU models with shorter time lags. Moreover, subgroup analyses reveal significant variations in predictive performance across age groups and disease categories, while emphasizing the need for tailored predictive models that consider individual characteristics and vulnerabilities. The identification of key environmental factors, particularly $PM_{2.5}$, PM_{10}, and NO_2 levels as critical determinants of mortality risk, enhances the relevance of the study and applicability of the findings to the public health sector, providing valuable insights for targeted interventions aimed at improving air quality and reducing mortality rates among specific population segments.

This study has some limitations. First, the analysis relied on a specific set of air pollution data and may not be generalizable to other regions or countries with different environmental and demographic characteristics.

Second, the study did not consider potentially confounding factors, such as socioeconomic status, lifestyle factors, and healthcare access, which are likely to influence mortality rates. Third, the potential for misclassification bias from population mobility. Our analysis is based on mortality data linked to the location of death, but some people may have recently moved to work in Bangkok and were not long-term residents. Their mortality could be misclassified as being linked to the local environment, even though their cumulative exposure history to air pollution in the city was short. This non-differential misclassification typically biases the results toward the null, thereby underestimating the true association. However, positive associations were still observable, suggesting that the link between air pollution and mortality is genuinely present.

Conclusion

This study demonstrated the potential of neural networks in predicting air pollution-related mortality rates in Bangkok, thereby highlighting key factors for model development. Future studies should focus on enhancing accuracy through advanced techniques and real-time data, as well as assessing model generalizability.

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Conflict of interest

The authors declare no competing interests.

Author contributions

Conceptualization, methodology, software, data analysis, and original manuscript drafting: Kanakorn Horsiritham. Data analysis and visualization: Natthaya Bunplod. Investigation, review, and editing: Patthrarawalai Sirinara, Perapong Tekasakul, and Sitthichok Chaichulee. Supervision, resources, and manuscript review and editing: Thammasin Ingviya.

Data availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

References

1. Sharma AK. Air pollution and health: ever widening spectrum. Indian Pediatr 2019;56:823-4. doi: 10.1007/s13312-019-1606-3.
2. The Lancet Planetary Health. The air that we breathe. Lancet Planet Health 2022;6:e1. doi: 10.1016/S2542-5196(21)00357-0.
3. Ambient (outdoor) air pollution. 2024 Oct 24. In: World Health Organization [homepage on the Internet]. Geneva: WHO, 2024. [cited 2025 Aug 9]. Available from: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.
4. Vichit-Vadakan N, Vajanapoom N. Health impact from air pollution in Thailand: current and future challenges. Environ Health Perspect 2011;119:A197-8. doi: 10.1289/ehp.1103728.
5. Uttamang P, Choomanee P, Phupijit J, Bualert S, Thongyen T. Investigation of secondary organic aerosol formation during O_3 and $PM_{2.5}$ episodes in Bangkok, Thailand. Atmosphere 2023;14:Article 6. doi: 10.3390/atmos14060994.
6. Ketjalan A, Humphries U, Suadee W. A study on $PM_{2.5}$ concentration in Bangkok, Thailand: A case study of Bang Na Station. Int J Adv Appl Sci 2023;10:55–61. doi: 10.21833/ijaas.2023.10.006.
7. Kallawicha K, Chompuchan C. Spatial distribution of $PM_{2.5}$ in Bangkok and its vicinity during 2011–2020. In: ISEE Conference Abstracts. Kaohsiung; ISEE Conference: 2023. doi: 10.1289/isee.2023.MP-009.
8. Ratanavalachai T, Trivitayanurak W. Application of a $PM_{2.5}$ dispersion model in the Bangkok central business district for

air quality management. Front Environ Sci 2023;11:1237366. doi: 10.3389/fenvs.2023.1237366.

9. Tesfaldet YT, Chanpiwat P. The effects of meteorology and biomass burning on urban air quality: the case of Bangkok. Urban Clim 2023;49:101441. doi: 10.1016/j.uclim.2023.101441.
10. Xu L, Chen B, Huang C, Zhou M, You S, Jiang F, et al. Identifying $PM_{2.5}$-related health burden in the context of the integrated development of urban agglomeration using remote sensing and GEMM model. Remote Sens 2023;15:2770. doi: 10.3390/rs15112770.
11. Balamurugan V, Chen J, Wenzel A, Keutsch FN. Spatiotemporal modeling of air pollutant concentrations in Germany using machine learning. Atmos Chem Phys 2023;23:10267-85. doi: 10.5194/acp-23-10267-2023.
12. Sun H, Chen S, Li X, Cheng L, Luo Y, Xie L. Prediction and early warning model of mixed exposure to air pollution and meteorological factors on death of respiratory diseases based on machine learning. Environ Sci Pollut Res 2023;30:53754-66. doi: 10.1007/s11356-023-26017-1.
13. Wan M, Archibald A. Neural network studies of air quality and socioeconomic predictors of mortality. In: EGU General Assembly Conference Abstracts. Vienna: EGU General Assembly 2023; 2023;p.24-8. doi: 10.5194/egusphere-egu23-1535.
14. Vichit-Vadakan N, Vajanapoom N, Ostro B. The public health and air pollution in Asia (PAPA) project: estimating the mortality effects of particulate matter in Bangkok, Thailand. Environ Health Perspect 2008;116:1179-82. doi: 10.1289/ehp.10849.
15. Buya S, Gokon H, Huynh VN, Dam HC, Usanavasin S, Karnjana J, Taneepanichskul N. Spatiotemporal association between monthly PM2.5 levels and cardiorespiratory mortality in Thailand (2015-2019). Int J Environ Health Res 2026;36:41-52. doi: 10.1080/09603123.2025.2458726.
16. Thongphunchung K, Charoensuk P, U-tapan S, Loonsamrong W, Phosri A, Mahikul W. Outpatient department visits and mortality with various causes attributable to ambient air pollution in the eastern economic corridor of Thailand. Int J Environ Res Public Health 2022;19:7683. doi: 10.3390/ijerph19137683.

Supplementary Table 1 Pollutant statistics

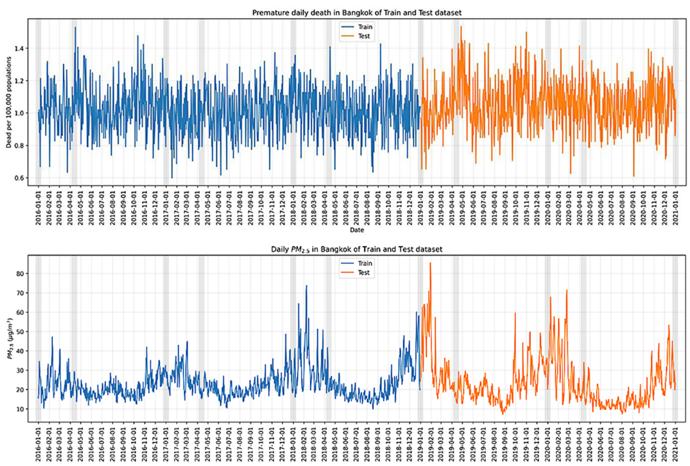
	Count	Median	Q1	Q3
dailyPM^{10} ($\mu g/m^3$)	1828	41.31	34.43	51.06
daily$PM_{2.5}$ ($\mu g/m^3$)	1828	20.9	16.78	26.89
dailyCO (ppb)	1828	0.67	0.56	0.79
dailySO_2 ($\mu g/m^3$)	1828	2.32	1.94	2.85
dailyNO_2 ($\mu g/m^3$)	1828	17.68	14.6	22.39
dailyO_3 ($\mu g/m^3$)	1828	21.69	18.9	25.26
dailyWS (km/h)	1828	1.01	0.87	1.17
dailyTemp (°C)	1828	29.51	28.75	30.17
dailyRH (%)	1828	71.37	67.44	74.6

Supplementary Table 2 Error analysis of young subgroup

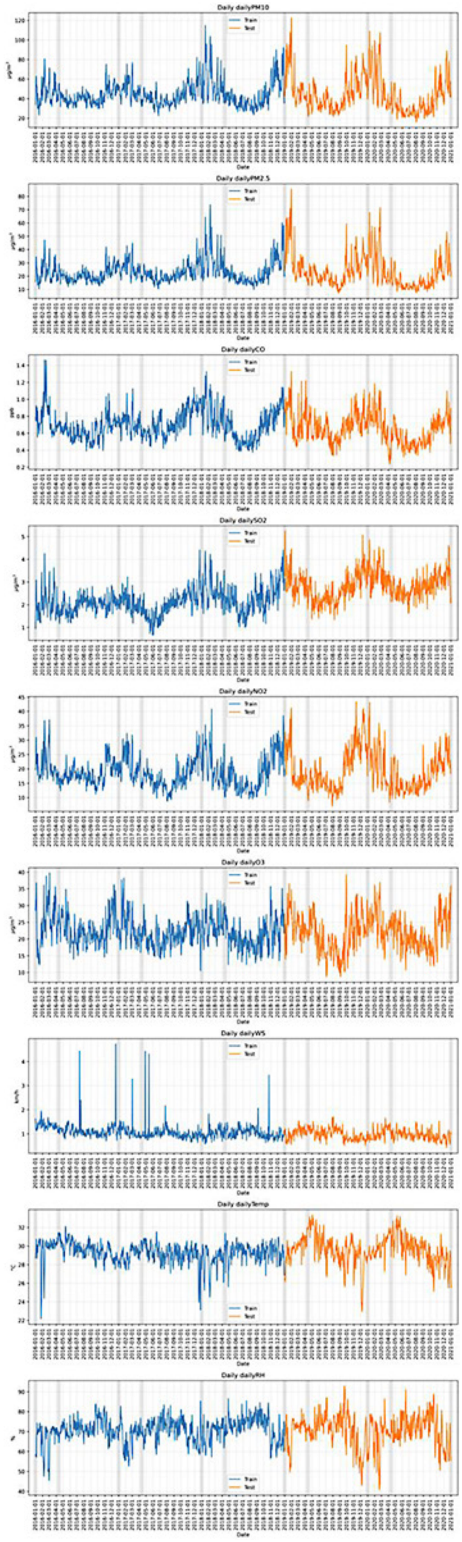
Chapter	Block	Title	Amount
Young subgroup (Total)			745
Diseases of the circulatory system (Congenital disorders)			192
	I20	Angina pectoris	35
	I46	Cardiac arrest	28
	I00	Rheumatic fever without mention of heart involvement	24
	I26	Pulmonary embolism	20
	I50	Heart failure	20
	Other		65

Supplementary Table 2 (continued)

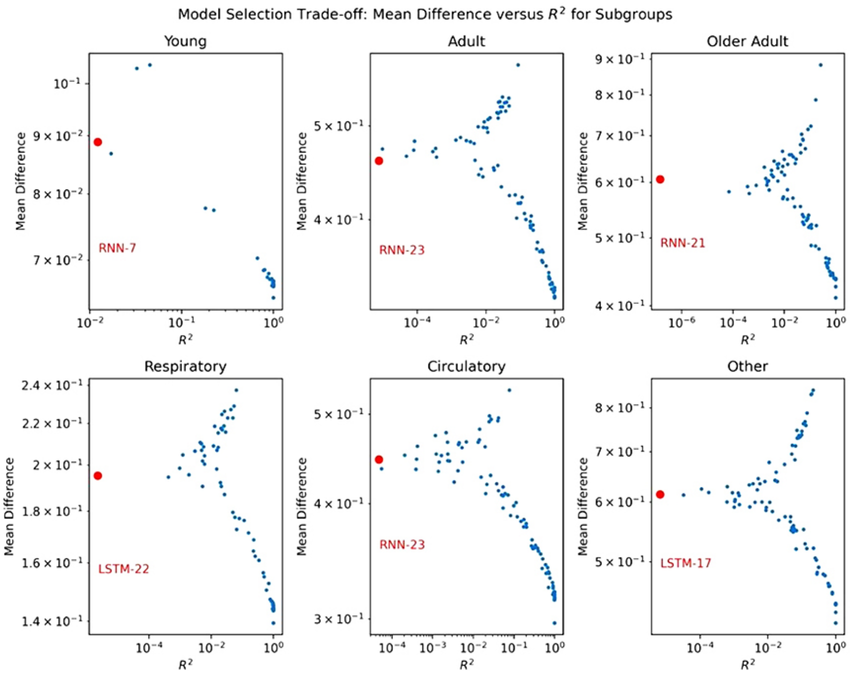
Chapter	Block	Title	Amount
Pregnancy, childbirth and the puerperium (Congenital disorders)			133
	O35	Maternal care for known or suspected abnormality of pelvic organs	105
	O00	Pregnancy with abortive outcome	13
	O95	Obstetric death of unspecified cause	3
	O80	Single spontaneous delivery	3
	O34	Maternal care for known or suspected abnormality of pelvic organs	2
	Other		7
Diseases of the respiratory system (Congenital disorders)			79
	J96	Respiratory failure, not elsewhere classified	20
	J95	Postprocedural respiratory disorders, not elsewhere classified	19
	J40	Bronchitis, not specified as acute or chronic	13
	J38	Diseases of vocal cords and larynx, not elsewhere classified	9
	J80	Adult respiratory distress syndrome	7
	Other		11
Certain infectious and parasitic diseases (Congenital disorders)			64
	A09	Other gastroenteritis and colitis of infectious and unspecified origin	26
	A00	Cholera	19
	A80	Acute poliomyelitis	8
	A02	Other salmonella infections	5
	A07	Other protozoal intestinal diseases	2
	Other		4
Congenital malformations, deformations, and chromosomal abnormalities (Congenital disorders)			63
	Q00	Anencephaly and similar malformations	28
	Q20	Congenital malformations of cardiac chambers and connections	11
	Q04	Other congenital malformations of the brain	9
	Q56	Indeterminate sex and pseudohermaphroditism	4
	Q26	Congenital malformations of great veins	4
	Other		7
Other			214



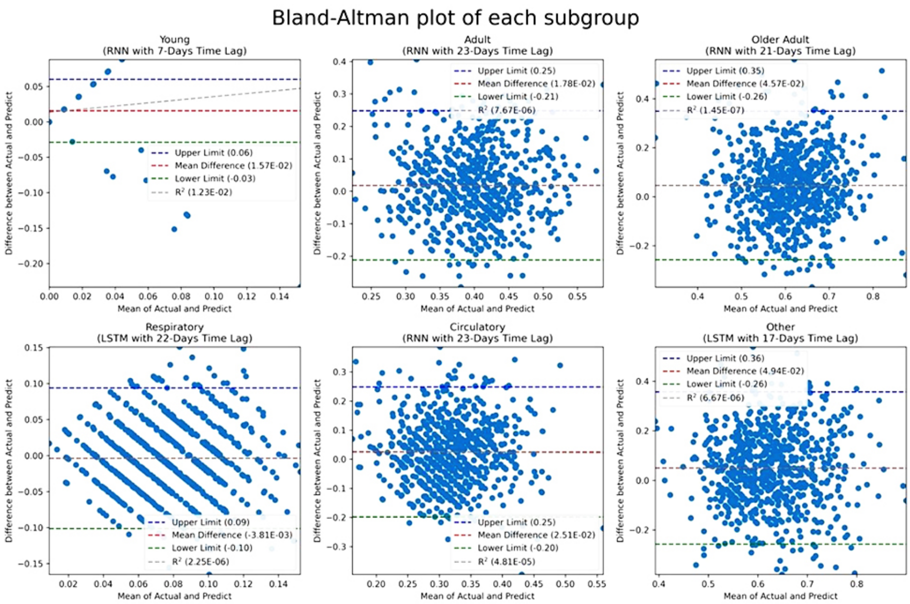
Supplementary Figure 1 Premature deaths and $PM_{2.5}$ in the Bangkok dataset



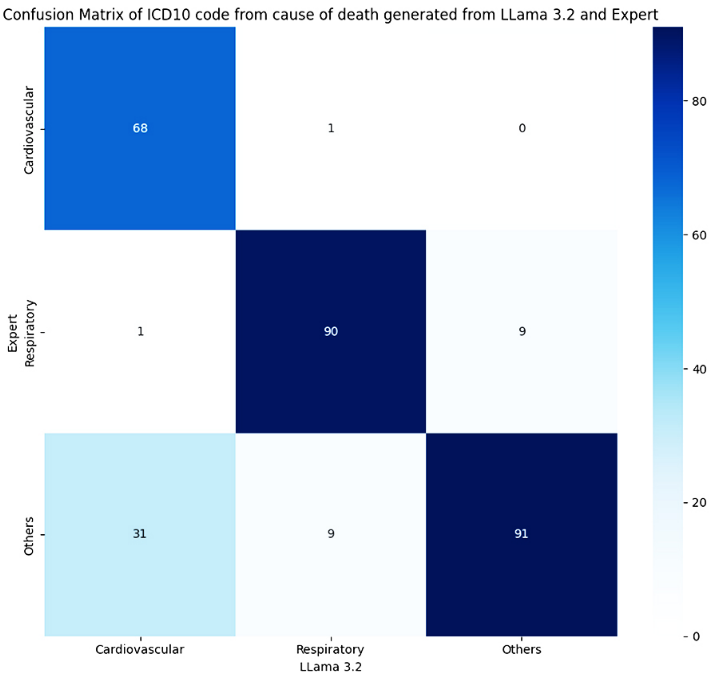
Supplementarty Figure 2 Training tests



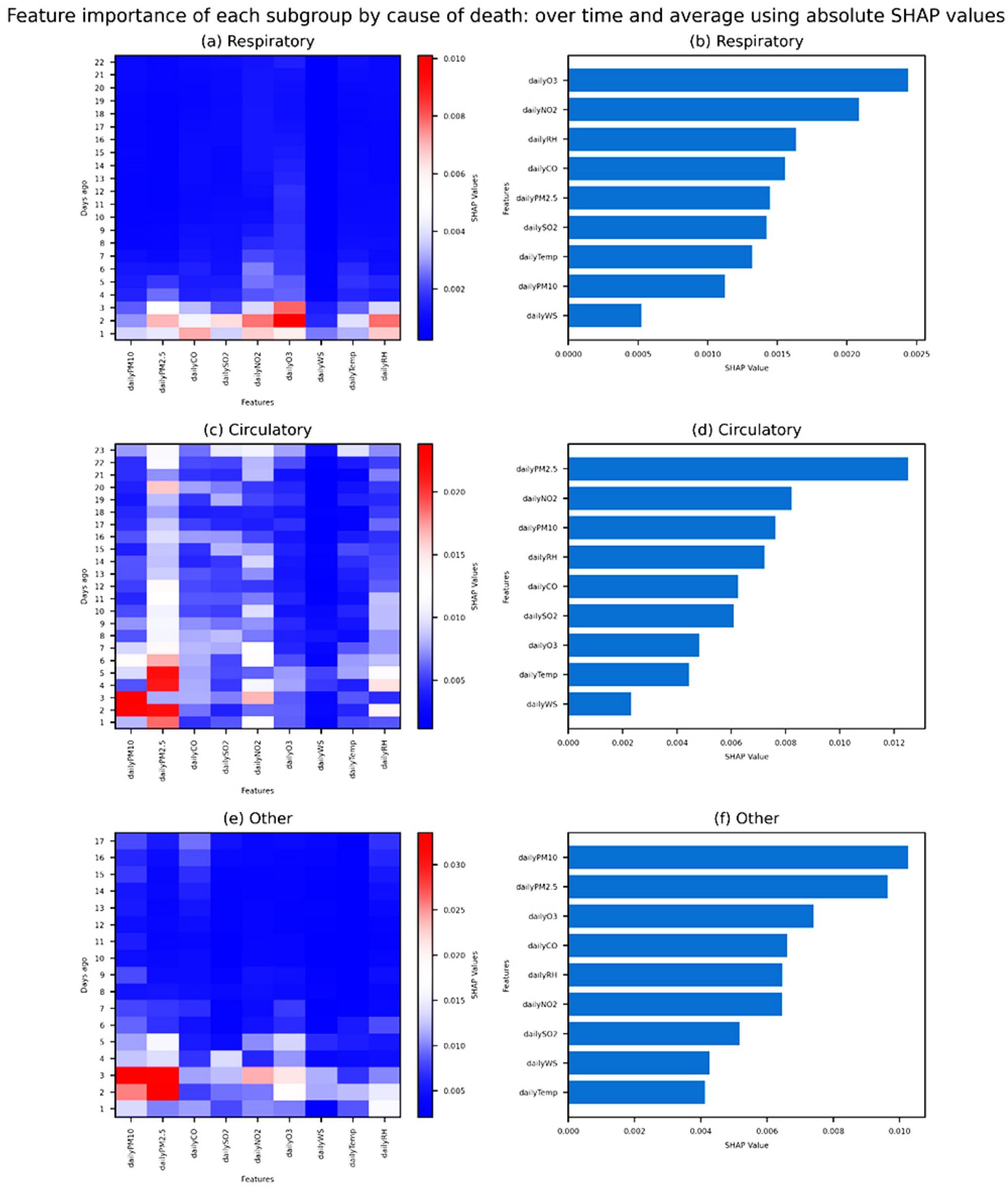
Supplementary Figure 3 Model selection trade-off: mean difference vs. R2 for subgroups



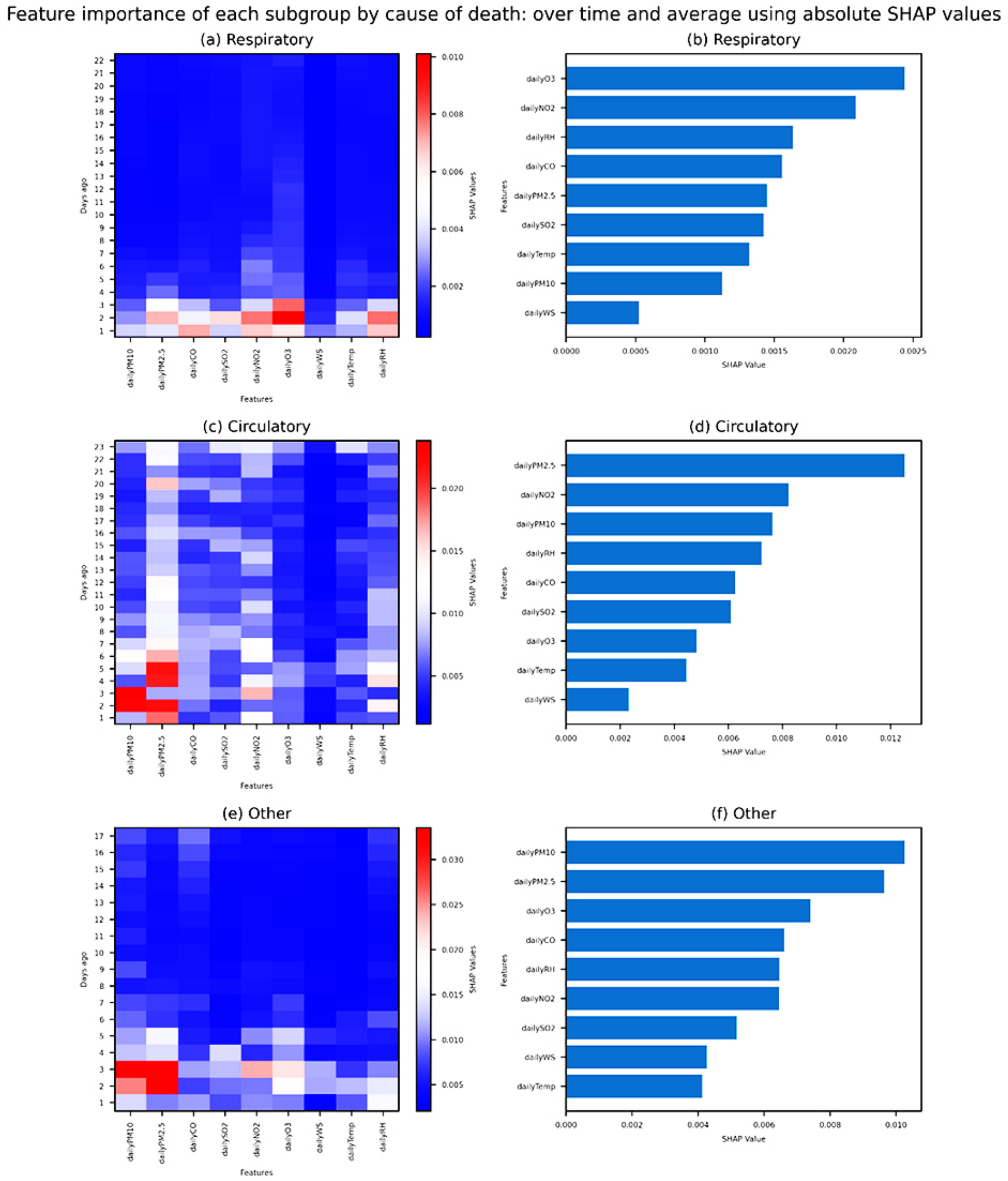
Supplementary Figure 4 Bland–Altman plot for each subgroup



Supplementary Figure 5 Model selection trade-off: mean difference vs. R2 for subgroups



Supplementary Figure 6 Feature importance of each subgroup by age: over time and average using absolute SHAP values. The figure illustrates how the influence of various environmental features on mortality prediction varies across different age groups, based on SHAP analysis. Panels (a) and (b) show that for the "Young" subgroup, daily relative humidity, NO_2, and PM_{10} were the most influential factors. Panels (c) and (d) reveal that the "Adult" subgroup was primarily affected by daily PM_{10}, NO_2, and $PM_{2.5}$, with notable impacts from a time lag of 10 to 17 days. Lastly, panels (e) and (f) indicate that for the "Older Adult" subgroup, the key influential factors were daily PM_{10}, $PM_{2.5}$, and CO, with a notable time-lagged impact occurring around 4 to 5 days after exposure.



Supplementary Figure 7 Feature importance of each subgroup by cause of death: over time and average using absolute SHAP values. The figure shows the varying influence of environmental factors on mortality across different causes of death, as determined by SHAP analysis. Panels (a) and (b) show that for the "Respiratory" subgroup, daily $PM_{2.5}$, NO_2, and PM_{10} were the most influential factors, with a notable impact from a time lag of 2 to 6 days. Panels (c) and (d) indicate that for the "Circulatory" subgroup, daily O_3, NO_2, and RH were the key drivers. Panels (e) and (f) reveal that the "Other" subgroup showed the strongest response to daily PM_{10}, $PM_{2.5}$, and CO, with a rapid impact felt within 2 to 3 days