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# Based on 'The Unity of Heaven and Man': Association Analysis between Air Pollution and Human Health in Beijing and Risk Prediction Using Automated Machine Learning

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**Abstract**

To investigate the correlations between air pollutants and hematological parameters, and to develop a risk prediction model for understanding the health impacts of air pollution, grounded in the traditional Chinese concept of "the unity of heaven and man."Data collected from 2019 to 2021 in the peripheral areas of Beijing were used. Six air pollutants ($PM_{2.5}$, $PM_{10}$, CO, $SO_2$, $NO_2$, $O_3$) and 13 hematological parameters (LYP, MONO, MONP, MP, EOSA, EOSP, BASO, BASOP, MCH, MCHC, SD, PDW, PCT) were analyzed. Analytical methods included Pearson correlation, two-tailed tests, three-dimensional clustering, nonmetric multidimensional scaling, variance partition analysis, redundancy analysis, and multi-group and two-group difference analysis. Automated machine learning (AutoML) was used to predict the trends of air pollutant impacts on health indicators. Long-term exposure to air pollutants was positively correlated with MP, BASO, LYP, and EOSP, and negatively correlated with MCH and PCT. Age emerged as a significant factor influencing health, whereas sex did not modify the effect of air pollution on health indicators. This study provides new evidence on air pollution induced health damage and offers novel insights into the underlying mechanisms of how air pollutants affect human health.

**Keywords:** The Unity of Heaven and Man; Air Pollution; Hematological Parameters; Risk Prediction

## 1. Introduction

Epidemiological studies have identified air pollution as a critical determinant of population health, associated with the development of various systemic diseases affecting the respiratory, immune, circulatory, reproductive, endocrine, and nervous systems (Karimi & Samadi, 2024; Nakhjirgan et al., 2023). The association with respiratory diseases is particularly pronounced; air pollution can trigger conditions such as upper respiratory tract infections (including acute rhinitis, acute pharyngitis, acute tonsillitis, and acute laryngitis), bronchial asthma, pneumonia, chronic obstructive pulmonary disease, and respiratory tract tumors (Forastiere, 2024; T. Liu et al., 2024). In 2019, the World Health Organization (WHO) identified air pollution as a major threat to human health, estimating that it contributes to 7 million premature deaths annually from diseases including cancer and cardiovascular and cerebrovascular conditions.

Humans exist within, and are inseparable from, the natural environment. Human physiological functions depend on air; thus, air pollution can harm human health to varying degrees. This principle resonates with "The Unity of Heaven and Man," a core concept of traditional Chinese culture that profoundly influences thought and behavior. Although the concept originates in the Book of Changes (Zhou Yi), its explicit articulation is credited to Zhang Zai of the Northern Song Dynasty: "The Confucian scholar attains sincerity through enlightenment and achieves enlightenment through sincerity, hence the unity of Heaven and Man." The Book of Changes portrays this unity as an integrated whole comprising "Heaven," "Earth," and "Man," encompassing both the internal unity of the human body and the close relationship between humans and nature. This holistic perspective, which is foundational to the theoretical system of traditional Chinese medicine, provides guidance for disease diagnosis and treatment. Although the Inner Canon of the Yellow Emperor (Nei Jing) does not explicitly use the term, the Spiritual Pivot (Ling Shu) describes life in terms of "man's correspondence with Heaven's Qi," indicating that changes in the natural environment influence human health and the onset of disease, with variations in vital signs reflecting environmental changes. When considering disease occurrence, progression, and treatment, it is important not only to maintain the body's internal equilibrium from physiological and pathological perspectives but also to emphasize harmony between humans and their social and natural environments. Therefore, investigating the impact of air pollution on human health can inform the development of effective prevention and treatment strategies for related diseases and provide guidance for population health management (Wang & Xue, 2026).

Ambient air contains numerous hazardous substances. In China, the Air Quality Index (AQI) is used to assess air quality based on six major pollutants: particulate matter with aerodynamic diameters of 10 μm or less ($PM_{10}$), fine particulate matter ($PM_{2.5}$), sulfur dioxide ($SO_2$), carbon monoxide (CO), ozone ($O_3$), and nitrogen dioxide ($NO_2$). Among these, particulate pollutants can remain suspended in the atmosphere for extended periods and readily adsorb harmful substances, such as heavy metals and microorganisms. When inhaled through the nose or mouth, they can contribute to diseases affecting multiple organ systems, making them important factors affecting population health in large and medium-sized cities (Wise et al., 2023). Although China has implemented multiple policies to prevent and control air pollution, further improvements are urgently needed. Various blood cells are essential for maintaining normal physiological functions.

Parameters measured in routine blood tests—including leukocyte, erythrocyte, and platelet indices—provide important information about human health, including immune status and hematological function (Foy et al., 2025). This study aims to investigate the impact of air pollutants on the health of populations in the peripheral areas of Beijing, providing evidence of air pollution-related health effects and informing disease prevention and control strategies.

## 2. Methodology

Basic data analysis was performed using Excel and Origin 2020. Relationships between variables were examined using IBM SPSS Statistics 25 through Pearson correlation analysis and two-tailed significance tests. Three-dimensional clustering and non-metric multidimensional scaling (NMDS) analyses, based on Bayesian distance algorithms, were conducted using EViews 11. Variance partitioning analysis (VPA) was performed using the "vegan" package in R. Redundancy analysis (RDA) was performed using CANOCO 4.5. Multigroup and two-group comparisons were conducted using STAMP software. Multigroup comparisons used analysis of variance (ANOVA) followed by the Tukey–Kramer post hoc test; two-group comparisons used the two-tailed Welch's t-test. The automated machine learning (AutoML) experiment used H2O on a system with the following specifications: operating system, Ubuntu 18.04 LTS; CPU, Intel Core i7-8700K at 3.70 GHz; and memory, 32 GB. The required software included Java 8, R 3.5.1, and H2O 3.22.1.6. Data preprocessing involved dividing the dataset into training and test sets and standardizing the data. Modeling was performed using the H2O AutoML algorithm through the following steps: initializing H2O, converting the data to H2O format, running the AutoML algorithm, and evaluating model performance (https://docs.h2o.ai/h2o/latest-stable/h2o-docs/automl.html).

### 2.1. Study Design

The data for this study were obtained from the "Air Pollution and Population Health Database" in the National Population Health Data Center Data Repository (PHDA; http://www.ncmi.cn). The original data were collected from residents in the peripheral areas of Beijing between January 2019 and December 2021, regardless of age, sex, or pre-existing medical conditions. The study received ethics committee approval. A professional team collected participants' personal information and biological samples, and qualified nurses collected blood samples. The initial dataset comprised 7,853 participants. After individuals with missing covariate data or outcome indicators were excluded, the final analytical sample consisted of 417 participants (Figure 1).

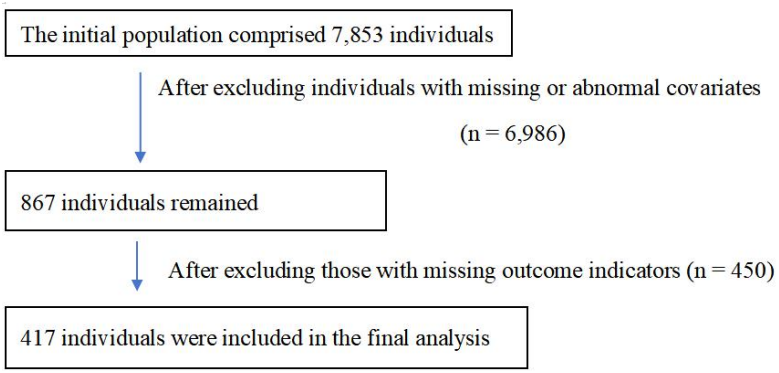


**Figure 1. Flowchart of data cleaning**

### 2.2. Human Health Indicator Assessment

Blood samples collected by qualified nurses were sent to a tertiary public hospital for routine blood analysis. This study focused on 13 hematological parameters: lymphocyte percentage (LYP), absolute monocyte count (MONO), monocyte percentage (MONP), neutrophil percentage (MP), absolute eosinophil count (EOSA), eosinophil percentage (EOSP), absolute basophil count (BASO), basophil percentage (BASOP), mean corpuscular hemoglobin (MCH), mean corpuscular hemoglobin concentration (MCHC), red blood cell distribution width (SD), platelet distribution width (PDW), and plateletcrit (PCT).

## 3. Results

### 3.1. Baseline Characteristics

Of the 417 participants, 237 (56.83%) were male and 180 (43.17%) were female. Participants ranged in age from 17 to 85 years and were distributed among four age groups: young adults, 112 (26.86%); early middle-aged adults, 81 (19.42%); middle-aged adults, 105 (25.18%); and older adults, 119 (28.54%). The relatively balanced distributions of sex and age in the study sample support the rationale for the analyses conducted (Table 1, Figure 2).

**Table 1. Baseline Characteristics**

| Variable | Category | n (%) |
|---|---|---|
| Gender | Male | 237（56.83%） |
| | Female | 180（43.17%） |
| Age | Range | 17-85 |
| | Young adults | 112（26.86%） |
| | Early middle-aged | 81（19.42%） |
| | Middle-aged | 105（25.18%） |
| | Older adults | 119（28.54%） |

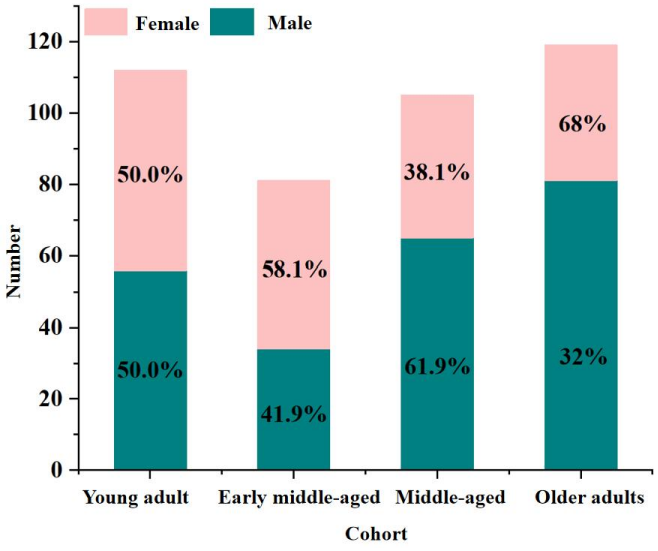


**Figure 2. Demographic characteristics of the study cohort**

### 3.2. Environmental Exposure

#### 3.2.1. Distribution of Air Pollutants

The median long-term exposure concentrations for the six pollutants—$PM_{2.5}$, $PM_{10}$, CO, $SO_2$, $NO_2$, and $O_3$—were 106.18 μg/m³, 161.14 μg/m³, 1.94 μg/m³, 49.79 μg/m³, 77.73 μg/m³, and 17.26 μg/m³, respectively. $PM_{10}$ had the highest reported concentration, whereas CO had the lowest (Figure 3).

#### 3.2.2. Correlation Analysis Between Air Pollutants

Correlation analysis revealed that, with the exception of $O_3$, the other five pollutants ($PM_{2.5}$, $PM_{10}$, CO, $SO_2$, and $NO_2$) were significantly positively correlated with one another ($p < .01$), whereas $O_3$ was significantly negatively correlated with each of the five pollutants ($p < .01$; Table 2, Figure 4).

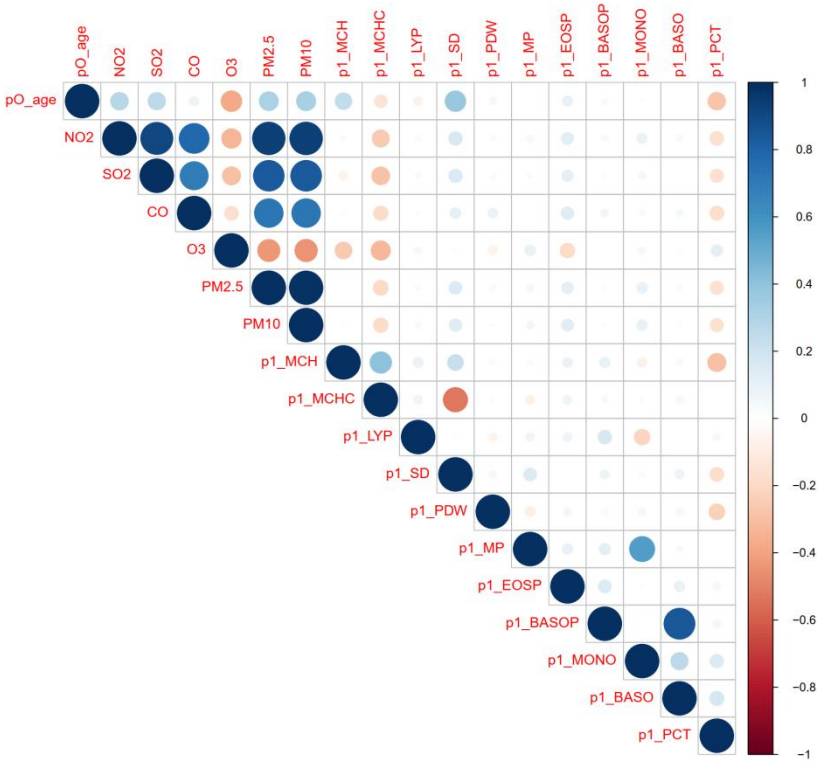


**Figure 4. Air pollutant correlation analysis**

Note: Correlation matrix and pairwise associations among PM2.5, PM10, CO, SO2, NO2, and O3.Positive correlations (P < 0.01): PM2.5 with PM10, CO, SO2, NO2; PM10 with CO, SO2, NO2; CO with SO2, NO2; SO2 with NO2.Negative correlations (P < 0.01): PM2.5 with O3; PM10, CO, SO2, and NO2 each with O3.

These findings are broadly consistent with previous research reporting strong positive correlations among $PM_{2.5}$, $PM_{10}$, $SO_2$, and CO. That research also reported negative correlations between these pollutants and $NO_2$ and $O_3$, as well as a positive correlation between $NO_2$ and $O_3$ (Li et al., 2023; Meo et al., 2024). In the present study, the pattern of correlations between $O_3$ and other pollutants differed from the patterns observed among the other pollutants. One possible explanation is that $O_3$ concentrations are strongly influenced by seasonal variations, with trends that may differ from those of other pollutants. Stronger associations involving other pollutants may also obscure the observed effects of $O_3$. A year-long field study of six air pollutants at 23 sampling sites in western China similarly demonstrated that $O_3$ concentrations varied inversely with those of other pollutants at low altitudes (Yang et al., 2020).

**Table 2. Air pollutant correlation analysis**

| Parameter | p0_gender | p0_age | p1_MCH | p1_MCHC | p1_LYP | p1_SD | p1_PDW | p1_MP | p1_EOSP | p1_BASOP | p1_MONO | p1_BASO | p1_PCT | PM2.5 | PM10 | $NO_2$ | $SO_2$ | CO | $O_3$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| p0_gender | 1.000 | -0.127** | -0.299** | -0.269** | 0.023 | 0.045 | -0.232** | -0.080 | -0.246** | -0.093 | -0.184** | -0.142** | 0.182** | -0.047 | -0.023 | -0.103* | -0.050 | -0.064 | 0.243** |
| p0_age | | 1.000 | 0.245** | -0.147** | -0.074 | 0.367** | 0.048 | -0.009 | 0.091 | 0.032 | -0.028 | -0.006 | -0.272** | 0.305** | 0.222** | 0.332** | 0.239** | 0.092 | -0.351** |
| p1_MCH | | | 1.000 | 0.415** | 0.099* | 0.222** | 0.016 | -0.039 | 0.081 | 0.092 | -0.083 | 0.043 | -0.289** | 0.019 | 0.001 | -0.007 | -0.076 | -0.014 | -0.222** |
| p1_MCHC | | | | 1.000 | 0.070 | -0.519** | 0.012 | -0.066 | 0.074 | -0.025 | -0.025 | -0.054 | -0.022 | -0.204** | -0.196** | -0.255** | -0.287** | -0.154** | -0.308** |
| p1_LYP | | | | | 1.000 | -0.010 | -0.049 | 0.065 | 0.069 | 0.166** | -0.206** | 0.004 | 0.029 | -0.009 | -0.199** | -0.051 | -0.027 | 0.002 | -0.055 |
| p1_SD | | | | | | 1.000 | -0.058 | 0.153** | 0.019 | 0.089 | 0.030 | 0.088 | -0.181** | 0.153** | 0.076 | 0.173** | 0.146** | 0.099* | 0.012 |
| p1_PDW | | | | | | | 1.000 | -0.070 | 0.067 | -0.020 | -0.031 | -0.033 | -0.231** | 0.064 | 0.023 | 0.072 | 0.033 | 0.090 | -0.056 |
| p1_MP | | | | | | | | 1.000 | 0.093 | 0.109* | 0.565** | 0.047 | 0.006 | 0.072 | -0.006 | 0.066 | 0.047 | 0.002 | 0.120* |
| p1_EOSP | | | | | | | | | 1.000 | 0.149** | 0.000 | 0.106* | -0.045 | 0.136** | 0.072 | 0.133** | 0.108* | 0.098* | -0.174** |
| p1_BASOP | | | | | | | | | | 1.000 | 0.013 | 0.861** | 0.060 | 0.037 | 0.039 | 0.043 | 0.020 | 0.038 | 0.007 |
| p1_MONO | | | | | | | | | | | 1.000 | 0.269** | 0.153** | 0.110* | 0.089 | 0.102* | 0.065 | 0.046 | 0.055 |
| p1_BASO | | | | | | | | | | | | 1.000 | 0.167** | 0.039 | 0.056 | 0.053 | 0.012 | 0.063 | 0.027 |
| p1_PCT | | | | | | | | | | | | | 1.000 | -0.160** | -0.154** | -0.187** | -0.164** | -0.152** | 0.131** |
| PM2.5 | | | | | | | | | | | | | | 1.000 | 0.791** | 0.857** | 0.801** | 0.648** | -0.338** |
| PM10 | | | | | | | | | | | | | | | 1.000 | 0.682** | 0.627** | 0.469** | -0.248** |
| $NO_2$ | | | | | | | | | | | | | | | | 1.000 | 0.804** | 0.677** | -0.289** |
| $SO_2$ | | | | | | | | | | | | | | | | | 1.000 | 0.601** | -0.271** |
| CO | | | | | | | | | | | | | | | | | | 1.000 | -0.185** |
| $O_3$ | | | | | | | | | | | | | | | | | | | 1.000 |

### 3.3. Distribution of Human Health Indicators

The median values of the human health indicators were as follows: LYP (32.6%), MONO (0.32 × 10⁹/L), MP (5.4%), EOSP (1.9%), BASO (0.02 × 10⁹/L), BASOP (40%), MCH (30.4 pg), MCHC (329 g/L), SD (41.2 fL), PDW (16%), and PCT (23%) (Figure 5).

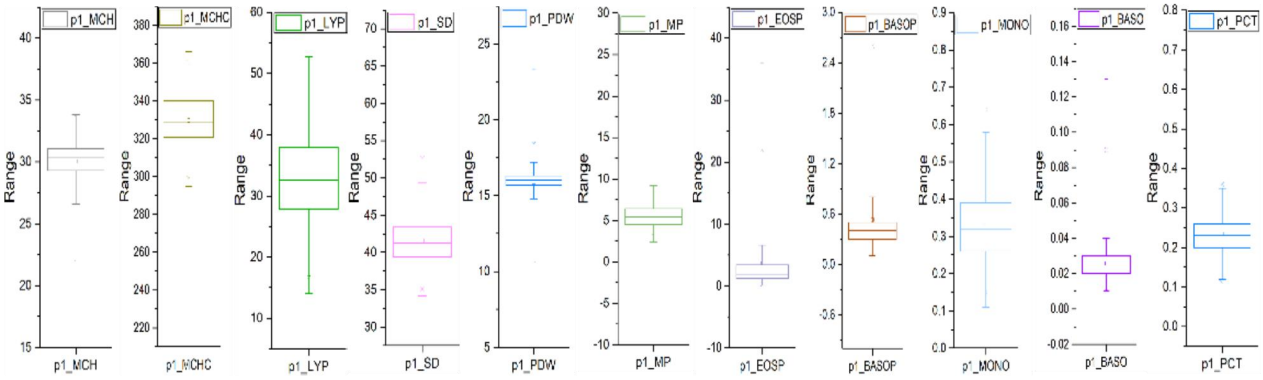


**Figure 5. Distribution of human health indicators**

Note: Median values (M) of human health indicators: LYP (32.6%), MONO (0.32 × 10⁹/L), MP (5.4%), EOSP (1.9%), BASO (0.02 × 10⁹/L), BASOP (40%), MCH (30.4 pg), MCHC (329 g/L), SD (41.2 fL), PDW (16%), and PCT (23%).

### 3.4. Intergroup Difference Analysis

#### 3.4.1. Sex-Based Group Difference Analysis

The results indicated that sex did not modify the associations between air pollutants and human health indicators. Studies specifically examining sex differences in the health effects of $O_3$ exposure remain limited. One previous study suggested that air pollution had a greater impact on hematological parameters in males (Qiu et al., 2023). Another study found that $O_3$ had a greater impact on blood pressure in males than in females (Hu et al., 2023). Research has also suggested that endocrine-disrupting chemicals present in particulate matter may interfere with hormonal signaling (Rudel & Perovich, 2009). The lack of observed sex-based differences in the present study may be attributable to the limited sample size (Figure 6).

#### 3.4.2. Age-Based Group Difference Analysis

Clustering of the four age groups (young adults, early middle-aged adults, middle-aged adults, and older adults) showed that the health profiles of the young adult and early middle-aged groups were the most similar in terms of their associations with air pollution. The older adult group showed the least similarity to the other age groups, although its profile was closer to that of the middle-aged group (Figure 7). This pattern suggests that as individuals age and physiological functions decline, they may become more susceptible to environmental influences. Although the precise biological mechanisms remain unclear, studies suggest that oxygen delivery capacity decreases with age and that hypoxia can increase red blood cell and hemoglobin production. From the perspective of traditional Chinese medicine, the Suwen · Shanggu Tianzhen Lun (Plain Questions · Discourse on Heavenly Truth in Ancient Times) describes how kidney qi changes across the lifespan, from flourishing to decline: “At seven years of age, a girl’s kidney qi becomes prosperous ... at forty-nine, the Ren meridian becomes deficient, the Tai Chong meridian declines and withers, and

Tiangui is exhausted"; and "At eight years of age, a boy's kidney qi becomes substantial ... at sixty-four, teeth and hair begin to fall out." These classical descriptions indicate that visceral functions and the states of qi and blood change at different stages of aging. In the present study, the age-stratified analysis likewise showed that the health profiles of young adults and early middle-aged adults were most similar in relation to air pollution, whereas older adults showed the least similarity to the other groups. This finding suggests that susceptibility to environmental factors may increase with age. It also resonates with the traditional Chinese medicine principle that "when healthy qi is stored internally, exogenous pathogens cannot invade." As individuals age, kidney essence and healthy qi are thought to decline, weakening the body's defensive and regulatory capacities and making it more vulnerable to exogenous pathogens, including air pollutants (Q. Wang, 2005). Contemporary research suggests that age-related mitochondrial dysfunction and accumulated oxidative stress reduce cellular tolerance to environmental pollutants, a finding consistent with the traditional Chinese medicine view that aging bodies are more vulnerable to pathogenic influences (López-Otín et al., 2023). Animal experiments have shown that exposure to diesel exhaust increases red blood cell counts and hemoglobin concentrations in rats and induces oxidative stress and imbalances in antioxidant defense enzymes. These findings provide cellular and molecular support for the observed age-related associations between air pollution and health indicators (Dziendzikowska et al., 2018).

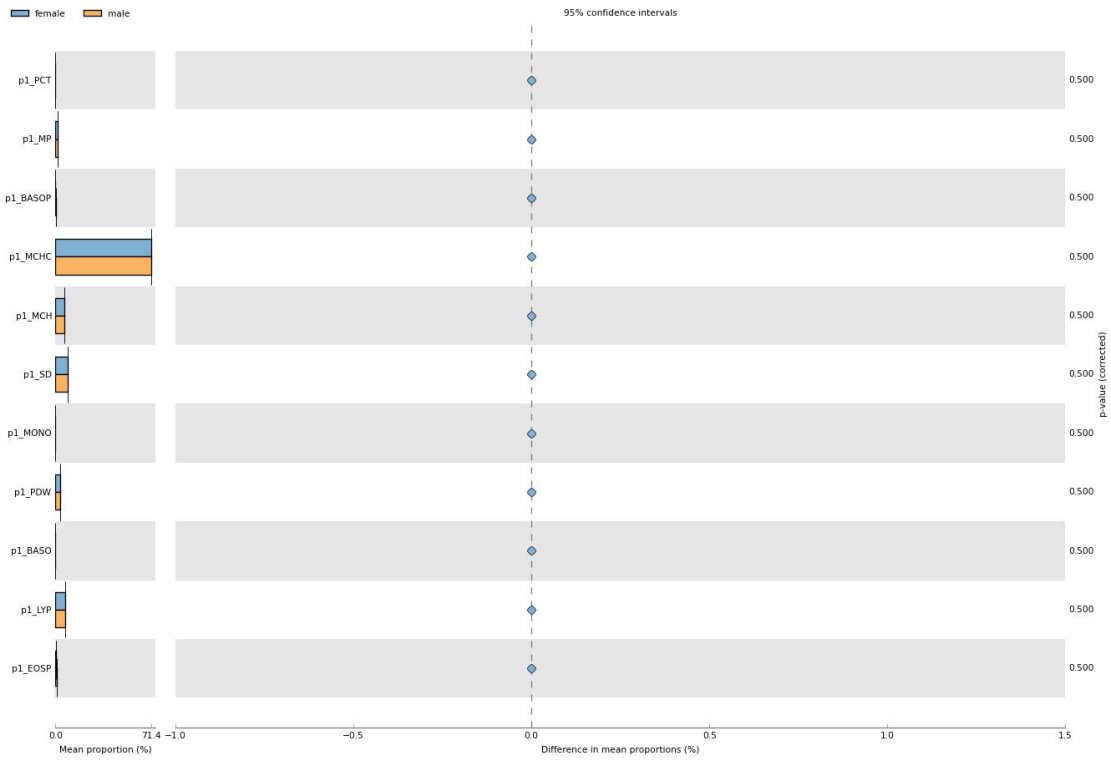


**Figure 6. Analysis of differences between gender groups**

Note: Sex-specific effects of ambient air pollutant exposure on human health indicators. No significant sex-related differences were observed in the associations between air pollutant exposure and health indicators.

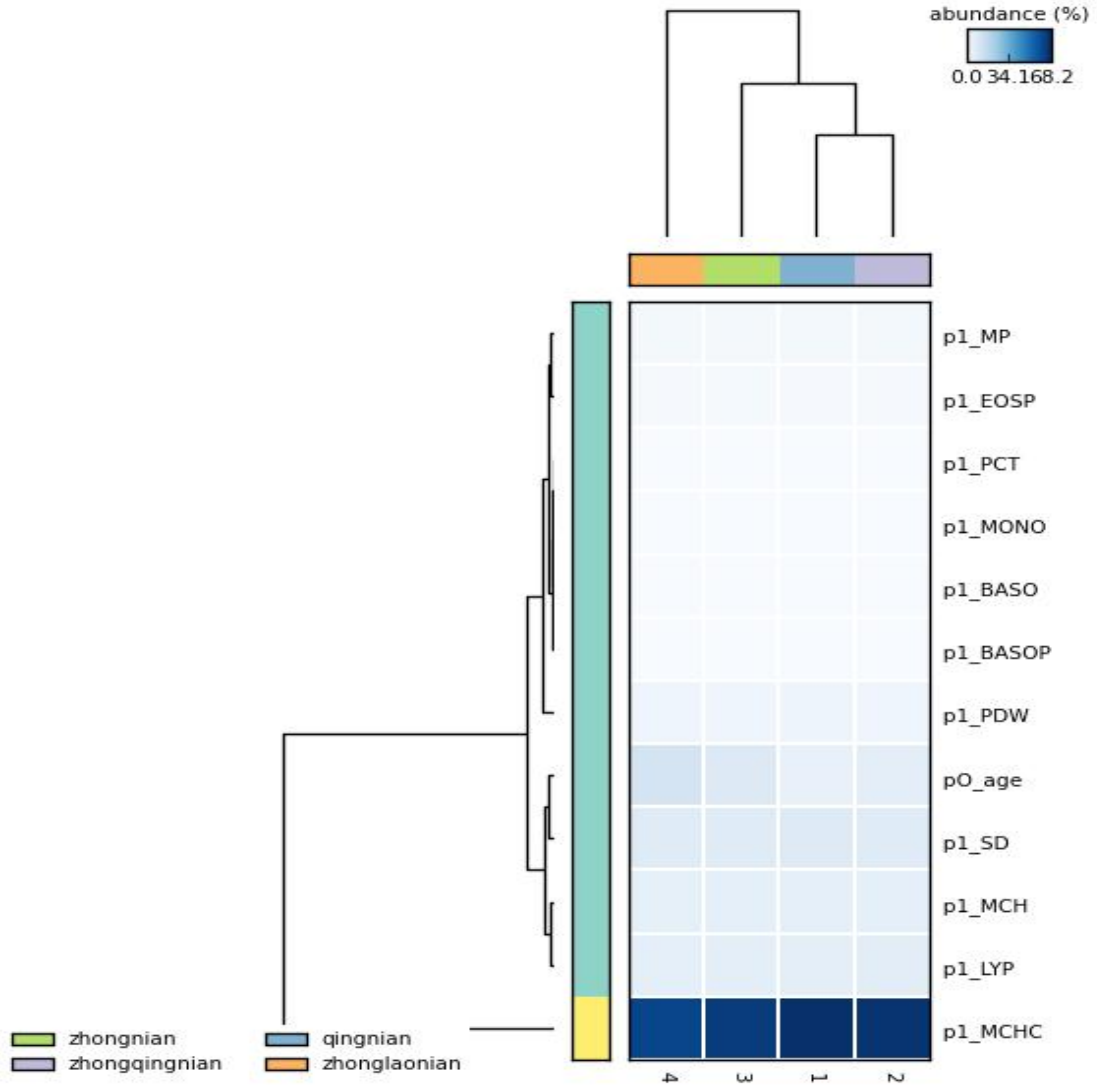


**Figure 7. Analysis of differences between age groups**

Note: Dendrogram of sample clustering by age subgroups (young adults, early middle-aged, middle-aged, and older adults) based on health effects of air pollutant exposure. Young adults and early middle-aged formed the closest cluster. Older adults were more distant from other groups, with the shortest distance to middle-aged adults.

### 3.5. RDA Analysis

Redundancy and cluster analyses were performed on the six air pollutants and 13 hematological parameters (Figure 8).

In the redundancy analysis of air pollutants, $NO_2$, CO, $SO_2$, and $PM_{10}$ clustered in the same quadrant, whereas $PM_{2.5}$ and $O_3$ were located in separate quadrants. Among the hematological parameters, PDW, EOSP, LYP, PCT, and MP were located in one quadrant; BASOP and BASO in another; and MCH and SD in a third.

Cluster analysis of air pollutants showed overlapping clusters for $NO_2$, CO, $SO_2$, $PM_{10}$, and $O_3$, whereas $PM_{2.5}$ formed a distinct, nonoverlapping cluster. Among the hematological parameters, SD, LYP, MCH, PDW, MP, and EOSP formed overlapping clusters; PCT, BASOP, and MONO formed another overlapping cluster; and BASO and MCHC appeared independently, without overlapping the other indicators.

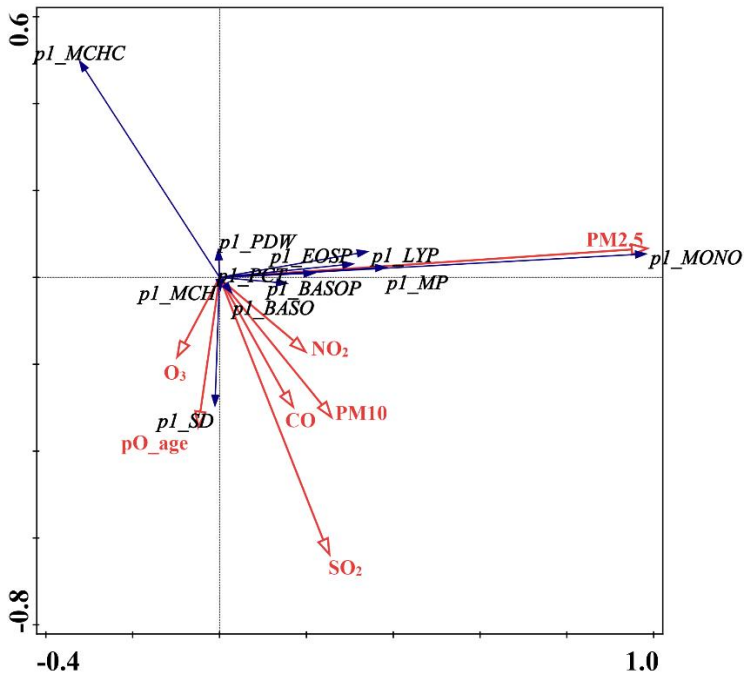


**Figure 8. RDA analysis**

Note: RDA: NO2, CO, SO2, PM10 in same quadrant; PM2.5 and O3 separate. Cluster: PM2.5 non-overlapping with others; health indicators: SD, LYP, MCH, PDW, MP, EOSP overlap; PCT, BASOP, MONO overlap; BASO and MCHC independent.

### 3.5.1. RDA of Air Pollutants

The pairwise association rankings derived from the analysis of air pollutants are presented in Figure 9.

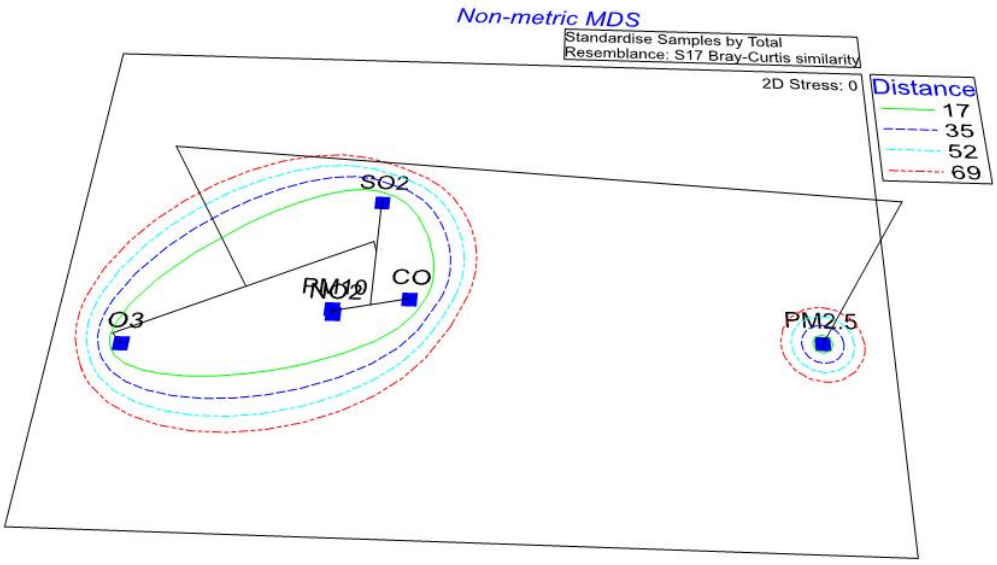


**Figure 9. RDA analysis of air pollutants**

Note: Pairwise association orders among NO2, PM10, CO, SO2, O3, and PM2.5 are indicated.

### 3.5.2. RDA of Human Health Indicators

A strong correlation was observed between LYP and SD, and both were moderately correlated with MCH. A weak correlation was found between MP and EOSP. Moderate correlations were also observed among PCT, BASO, and MONO (Figure 10).

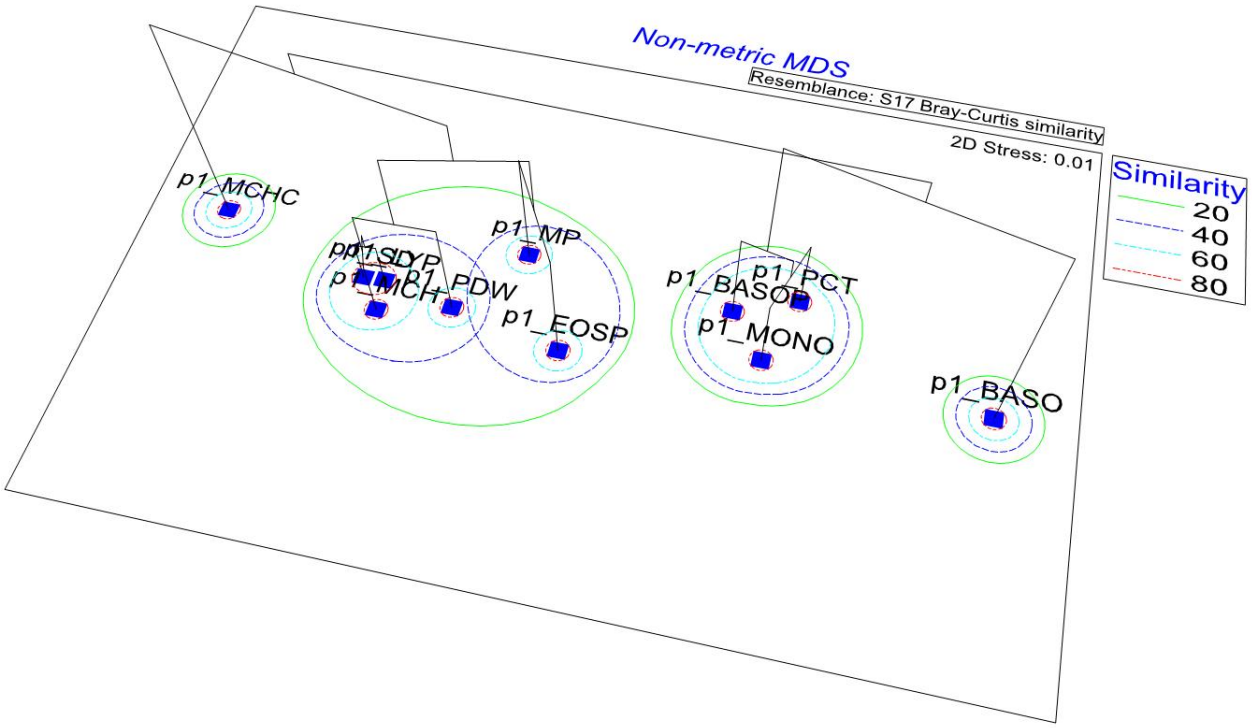


**Figure 10. RDA analysis of human health indicators**

Note: RDA of health indicators: LYP–SD high correlation; both with MCH moderate; MP–EOSP mild; PCT–BASO–MONO moderate.

### 3.5.3. Correlation Analysis Between Air Pollutant Exposure and Human Health

Increases in $PM_{2.5}$ were associated with significant increases in MONO, PDW, EOSP, LYP, MP, and BASOP, with the strongest correlation observed for MONO. Increases in CO, $PM_{10}$, $NO_2$, $SO_2$, and $O_3$ were associated with higher SD values. MCHC showed the weakest correlations with air pollutants.

## 3.6. Variance Partition Analysis (VPA)

Factors influencing human health indicators were classified into two groups: air pollution factors and individual baseline characteristics. VPA revealed that air pollution explained 3% of the variance in routine blood parameters, whereas individual baseline characteristics accounted for 2%. The remaining 95% of the variance was unexplained by these two groups of factors (Figure 11). This finding can be considered in relation to the cosmological perspective embedded in traditional Chinese culture. The theory of the "correspondence between Heaven and Man" views "Heaven" as the "macrocosm" and "Man" as the "microcosm." Traditional Chinese medicine regards humans as unified organisms integrating the physical body and spirit, analogous to a microcosm of nature. Human life is sustained by interconnected internal structures and functions, which also interact with the natural world. Accordingly, human physiological and pathological phenomena can be understood as arising from the combined influences of "Heaven," "Earth," and "Man"—that is, interactions between the natural environment and human physiological functions (Li et al., 2022).

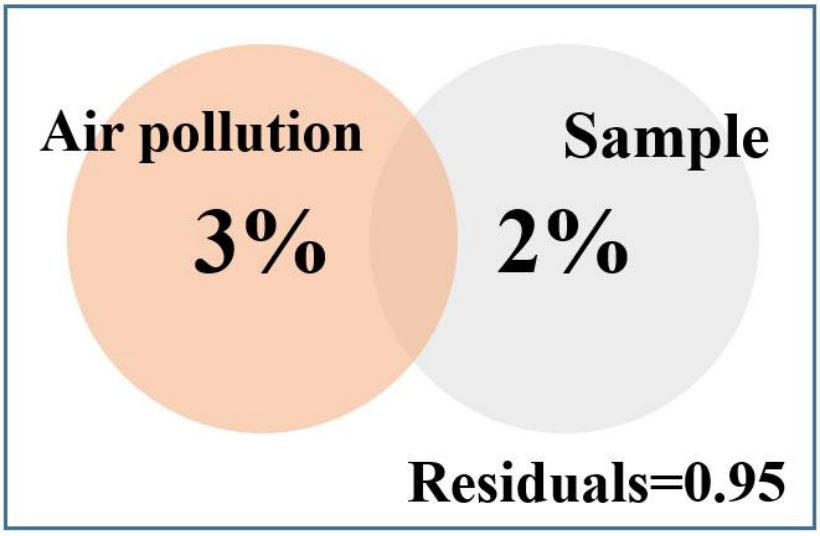


**Figure 11. Variance decomposition analysis (VDA)**

Note: Influence proportions: air pollution (3%), individual baseline information (2%), and multi-level comprehensive factors (95%).

## 3.7. Correlations Between Exposure to Individual Air Pollutants and Human Health Indicators

### 3.7.1. Impact of Air Pollutants on Human Immune Function

Higher $NO_2$ exposure was positively associated with lymphocyte levels. Monocyte levels were positively associated with exposure to $NO_2$, $SO_2$, and $O_3$. Eosinophil levels were positively associated with $PM_{2.5}$ and $SO_2$ exposure, whereas basophil levels were positively associated with $PM_{10}$, $NO_2$, and $O_3$ exposure (Deng et al., 2022; Lee et al., 2020; Liu et al., 2020; Liu et al., 2024; Qian et al., 2024; Salcan & Salcan, 2023; Sun et al., 2024; Zhong et al., 2024) (Table 3).

### 3.7.2. Impact of Air Pollutants on Erythroid Parameters

Increased exposure to $PM_{2.5}$, $PM_{10}$, $SO_2$, CO, and $O_3$ was associated with lower mean corpuscular hemoglobin concentration (MCHC) (Morales-Ancajima et al., 2019; Odo et al., 2023).

### 3.7.3. Impact of Air Pollutants on Coagulation Function

Platelet levels were inversely associated with $PM_{10}$, $NO_2$, $SO_2$, and CO exposure but positively associated with $O_3$ exposure (Krishnan et al., 2013; Liu et al., 2024; Wylie et al., 2017).

## 3.8. Automated Machine Learning Prediction Models

### 3.8.1. Variable Importance Analysis for Hematological Parameters

The input variables were ranked by their permutation-based importance for predicting hematological parameters, as follows:

(1) For MCH, age had the greatest importance, followed by sex, $PM_{2.5}$, $O_3$, $SO_2$, $NO_2$, CO, and $PM_{10}$ (Figure 12).

(2) For LYP, age had the greatest importance, followed by $O_3$, $SO_2$, $PM_{10}$, CO, $PM_{2.5}$, sex, and $NO_2$ (Figure 13).

(3) For SD, age had the greatest importance, followed by CO, $SO_2$, $O_3$, $NO_2$, sex, $PM_{10}$, and $PM_{2.5}$ (Figure 14).

(4) For PCT, CO had the greatest importance, followed by age, $PM_{10}$, sex, $NO_2$, $O_3$, $SO_2$, and $PM_{2.5}$ (Figure 15).

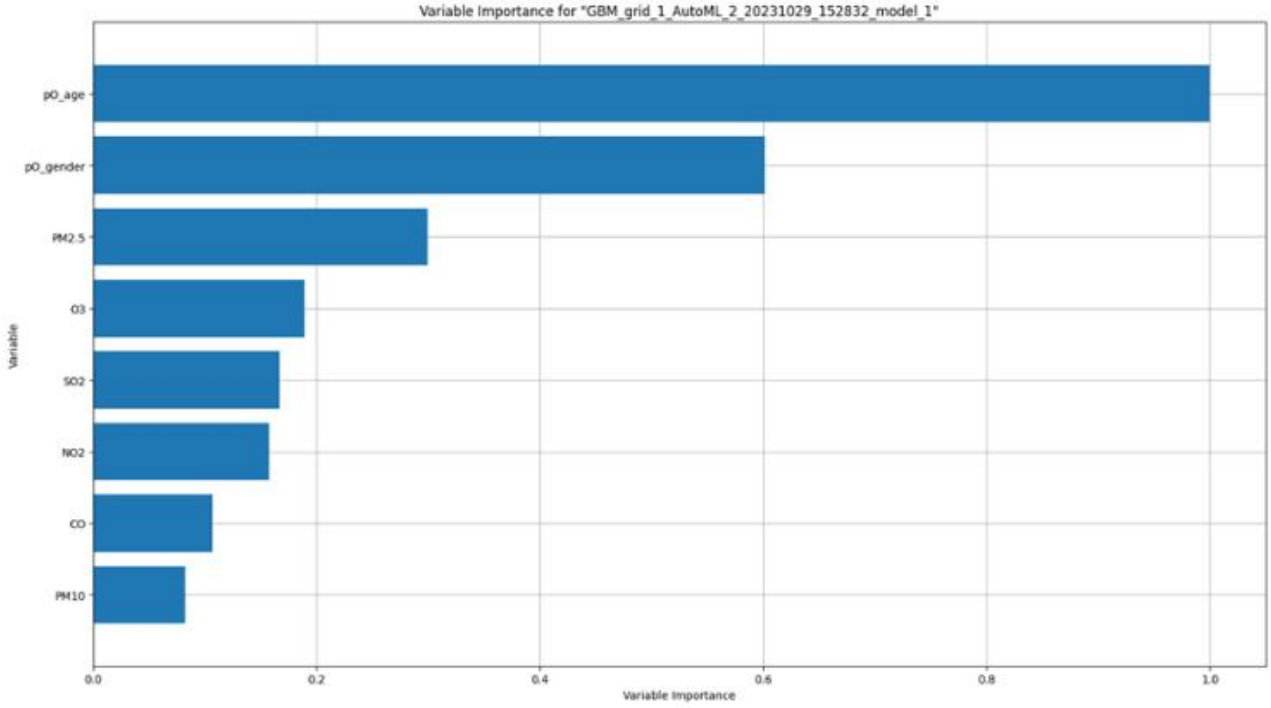


**Figure 12. Variable importance for MCH**

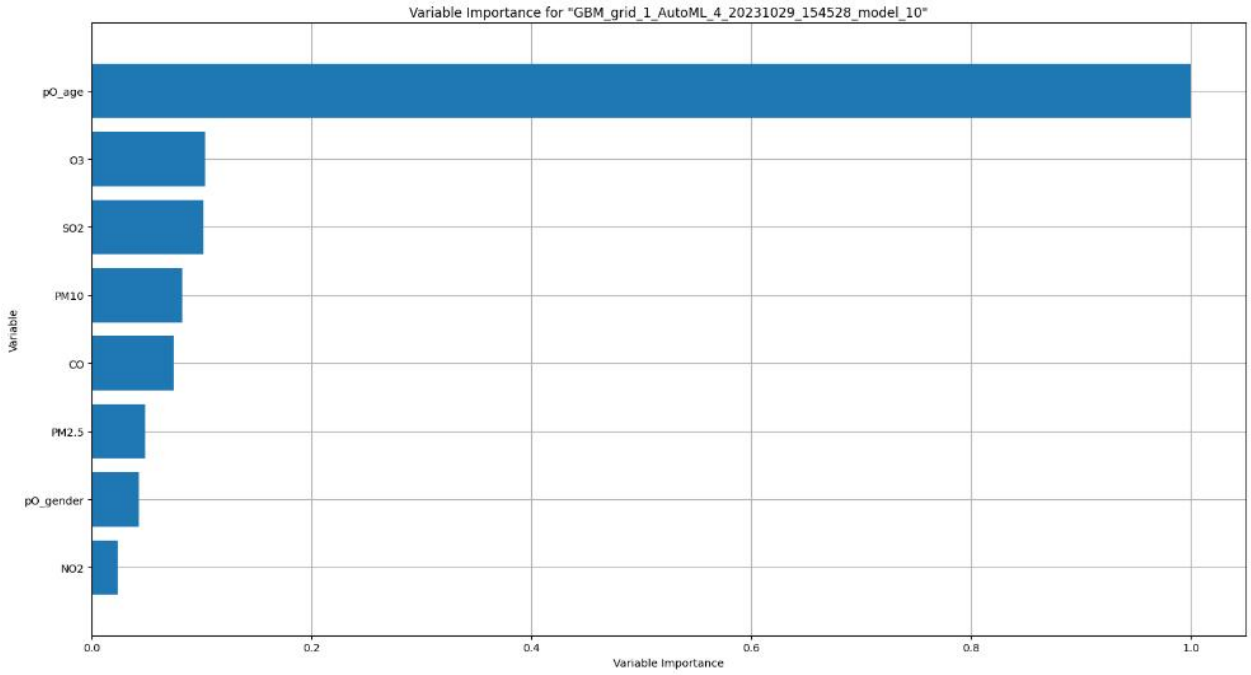


**Figure 13. Variable importance for LYP**

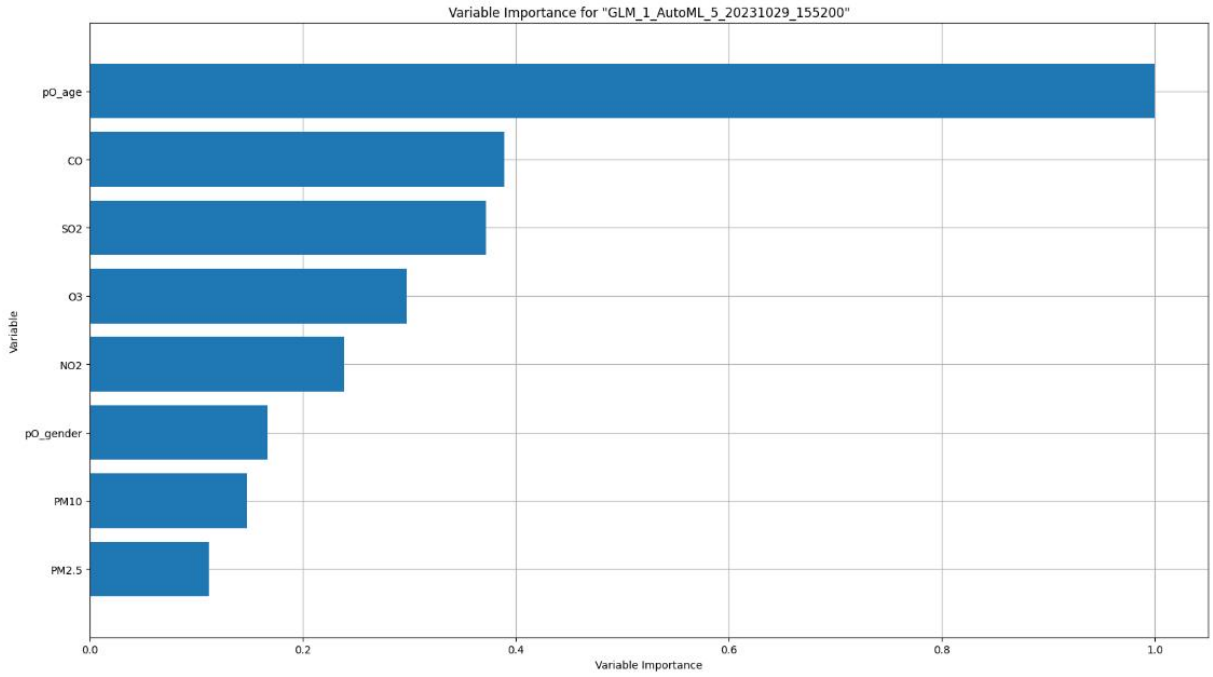


**Figure 14. Variable importance for SD**

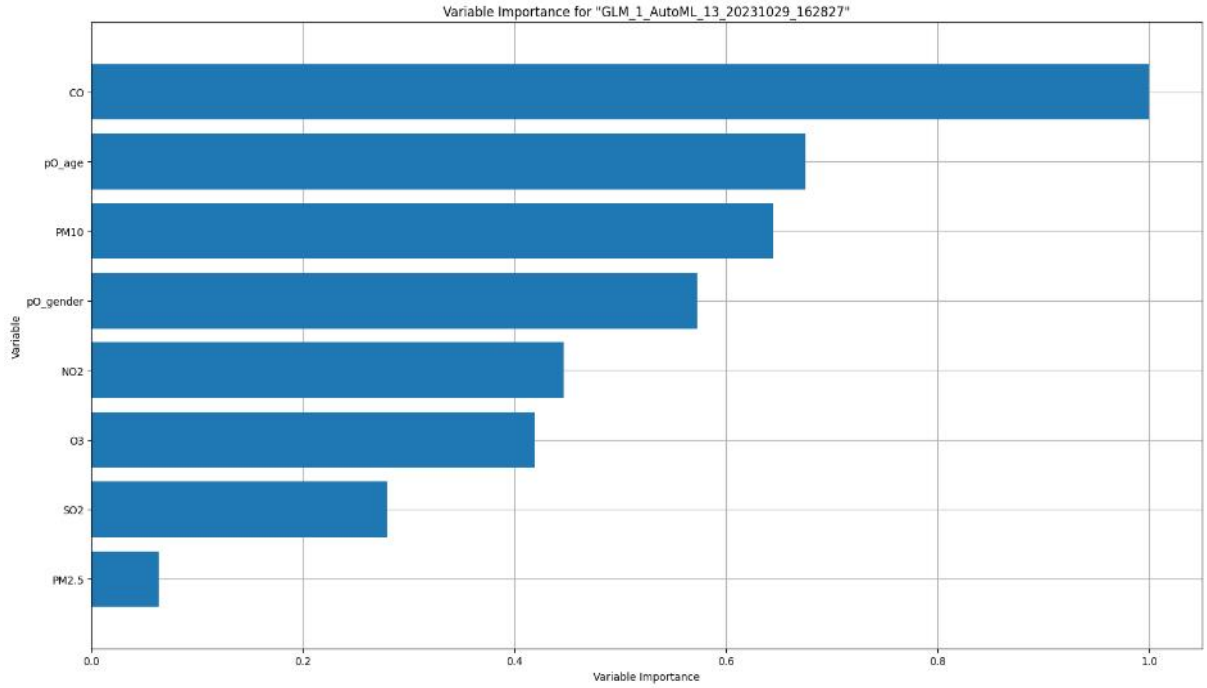


**Figure 15. Variable importance for PCT**

**Table 3. Correlations between exposure to single air pollutants and human health indicators**

| Parameter | p0_gender | p0_age | p1_MCH | p1_MCHC | p1_LYP | p1_SD | p1_PDW | p1_MP | p1_EOSP | p1_BASOP | p1_MONO | p1_BASO | p1_PCT | PM2.5 | PM10 | $NO_2$ | $SO_2$ | CO | $O_3$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| p0_gender | 1.000 | -0.127** | -0.299** | -0.269** | 0.023 | 0.045 | -0.232** | -0.080 | -0.246** | -0.093 | -0.184** | -0.142** | 0.182** | -0.047 | -0.023 | -0.103* | -0.050 | -0.064 | 0.243** |
| p0_age | | 1.000 | 0.245** | -0.147** | -0.074 | 0.367** | 0.048 | -0.009 | 0.091 | 0.032 | -0.028 | -0.006 | -0.272** | 0.305** | 0.222** | 0.332** | 0.239** | 0.092 | -0.351** |
| p1_MCH | | | 1.000 | 0.415** | 0.099* | 0.222** | 0.016 | -0.039 | 0.081 | 0.092 | -0.083 | 0.043 | -0.289** | 0.019 | 0.001 | -0.007 | -0.076 | -0.014 | -0.222** |
| p1_MCHC | | | | 1.000 | 0.070 | -0.519** | 0.012 | -0.066 | 0.074 | -0.025 | -0.025 | -0.054 | -0.022 | -0.204** | -0.196** | -0.255** | -0.287** | -0.154** | -0.308** |
| p1_LYP | | | | | 1.000 | -0.010 | -0.049 | 0.065 | 0.069 | 0.166** | -0.206** | 0.004 | 0.029 | -0.009 | -0.199** | -0.051 | -0.027 | 0.002 | -0.055 |
| p1_SD | | | | | | 1.000 | -0.058 | 0.153** | 0.019 | 0.089 | 0.030 | 0.088 | -0.181** | 0.153** | 0.076 | 0.173** | 0.146** | 0.099* | 0.012 |
| p1_PDW | | | | | | | 1.000 | -0.070 | 0.067 | -0.020 | -0.031 | -0.033 | -0.231** | 0.064 | 0.023 | 0.072 | 0.033 | 0.090 | -0.056 |
| p1_MP | | | | | | | | 1.000 | 0.093 | 0.109* | 0.565** | 0.047 | 0.006 | 0.072 | -0.006 | 0.066 | 0.047 | 0.002 | 0.120* |
| p1_EOSP | | | | | | | | | 1.000 | 0.149** | 0.000 | 0.106* | -0.045 | 0.136** | 0.072 | 0.133** | 0.108* | 0.098* | -0.174** |
| p1_BASOP | | | | | | | | | | 1.000 | 0.013 | 0.861** | 0.060 | 0.037 | 0.039 | 0.043 | 0.020 | 0.038 | 0.007 |
| p1_MONO | | | | | | | | | | | 1.000 | 0.269** | 0.153** | 0.110* | 0.089 | 0.102* | 0.065 | 0.046 | 0.055 |
| p1_BASO | | | | | | | | | | | | 1.000 | 0.167** | 0.039 | 0.056 | 0.053 | 0.012 | 0.063 | 0.027 |
| p1_PCT | | | | | | | | | | | | | 1.000 | -0.160** | -0.154** | -0.187** | -0.164** | -0.152** | 0.131** |
| PM2.5 | | | | | | | | | | | | | | 1.000 | 0.791** | 0.857** | 0.801** | 0.648** | -0.338** |
| PM10 | | | | | | | | | | | | | | | 1.000 | 0.682** | 0.627** | 0.469** | -0.248** |
| $NO_2$ | | | | | | | | | | | | | | | | 1.000 | 0.804** | 0.677** | -0.289** |
| $SO_2$ | | | | | | | | | | | | | | | | | 1.000 | 0.601** | -0.271** |
| CO | | | | | | | | | | | | | | | | | | 1.000 | -0.185** |
| $O_3$ | | | | | | | | | | | | | | | | | | | 1.000 |

### 3.8.2. Automated Machine Learning Predictions

Partial dependence plots (PDPs) illustrate the marginal association between an individual feature and a machine learning model's predictions, showing whether the relationship is linear, monotonic, or more complex. Steeper PDP curves indicate a greater change in the predicted outcome across the observed range of a feature, whereas flatter curves indicate a smaller change. The results were as follows (Figure 16-21):

(1) Age and $SO_2$ were important predictors of MCH. MCH levels tended to increase with age, whereas higher $SO_2$ concentrations were associated with lower MCH levels.

(2) Age and CO were important predictors of LYP. Predicted LYP levels decreased with increasing age and CO concentration.

(3) Age was an important predictor of SD; predicted SD levels increased with age.

(4) Age was an important predictor of PCT; predicted PCT levels decreased with age.

The AutoML analyses identified age as a major predictor of several hematological indicators. Biological aging is characterized by a progressive decline in physiological functions, and the model predictions are broadly consistent with this pattern. However, differences between the AutoML predictions and the results of correlation analyses may reflect the limited sample size and heterogeneity in participants' baseline health status.

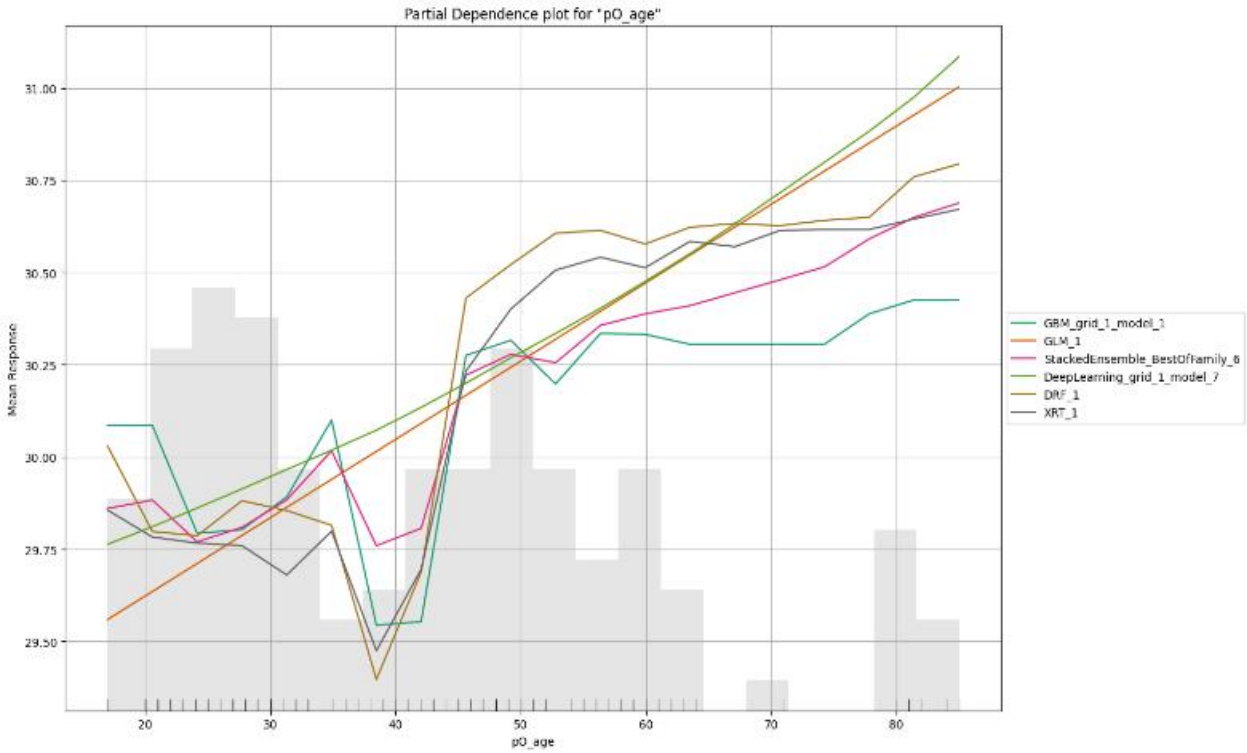


**Figure 16. The degree of influence of age on MCH**

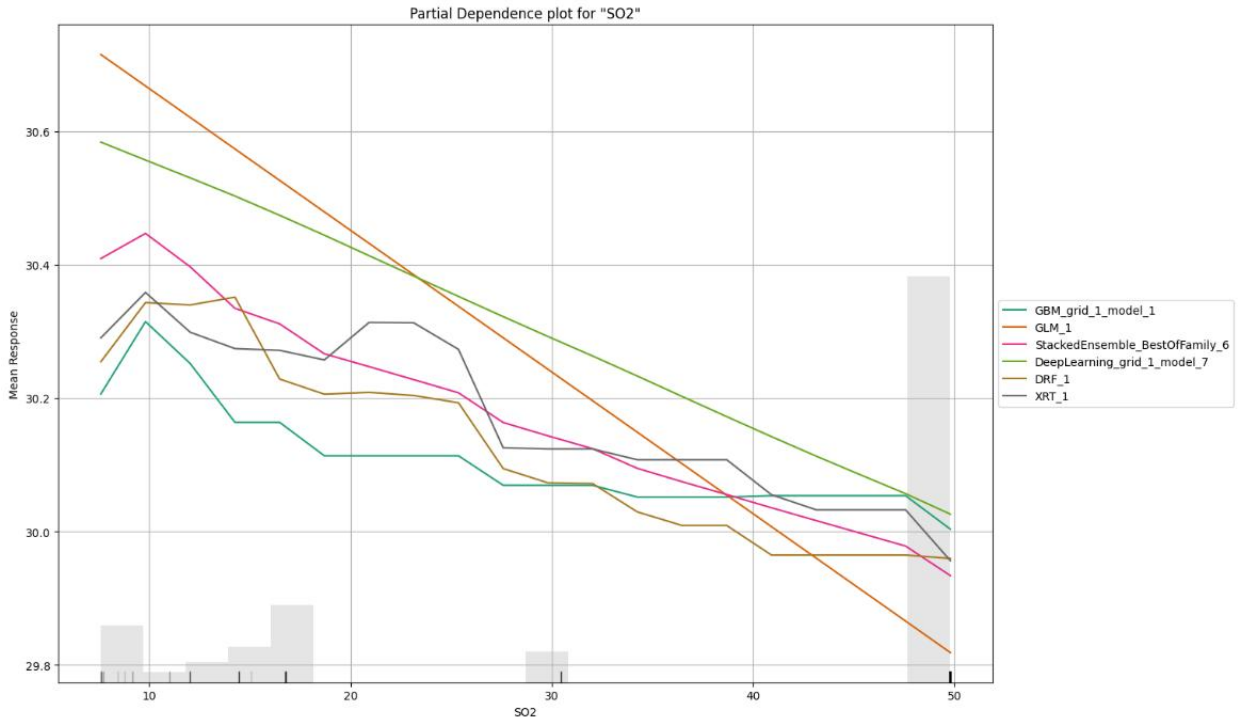


**Figure 17. The effect of $SO_2$on MCH levels**

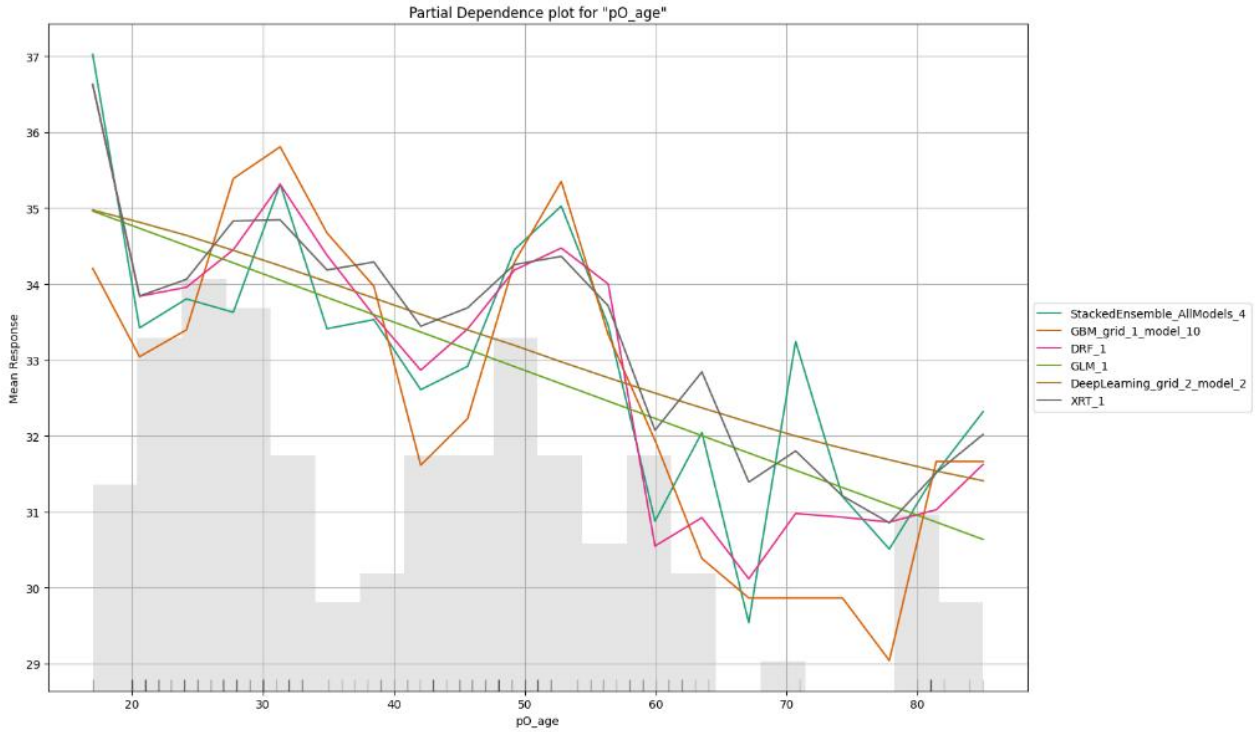


**Figure 18. The effect of age on LYP levels**

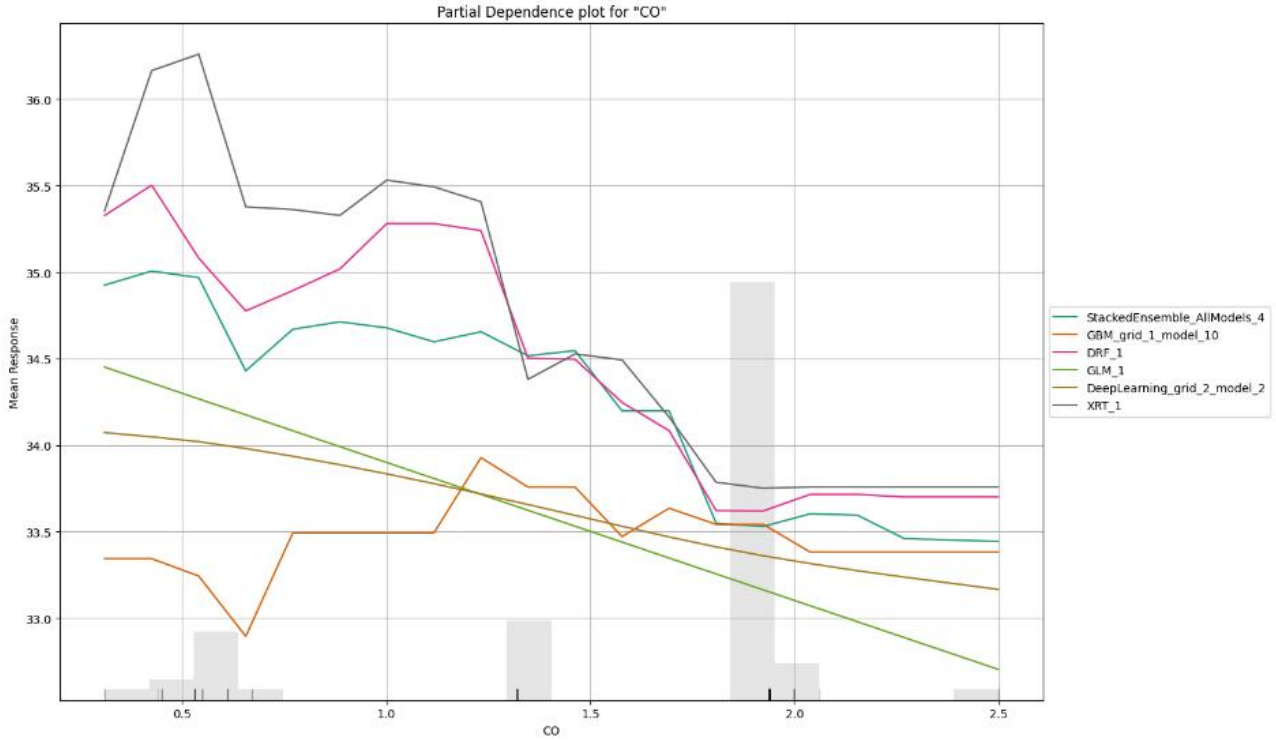


**Figure 19. The effect of CO on LYP levels**

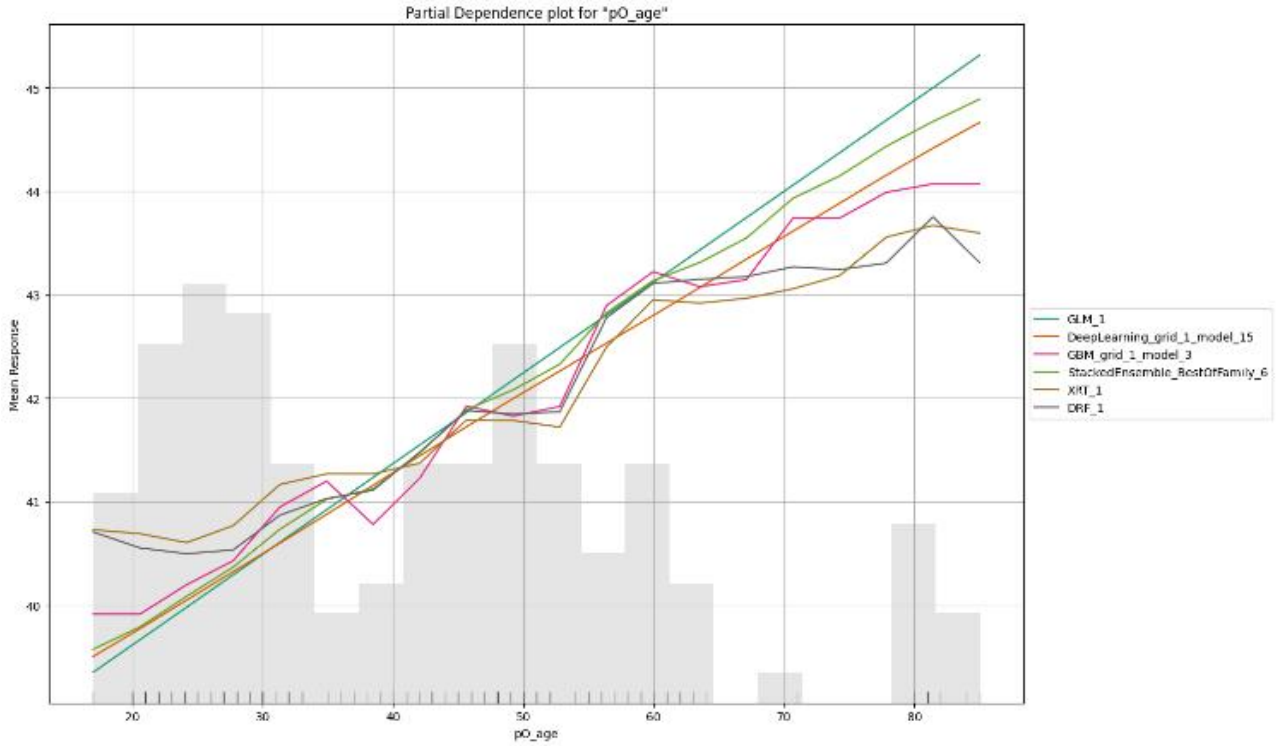


**Figure 20. The effect of age on SD levels**

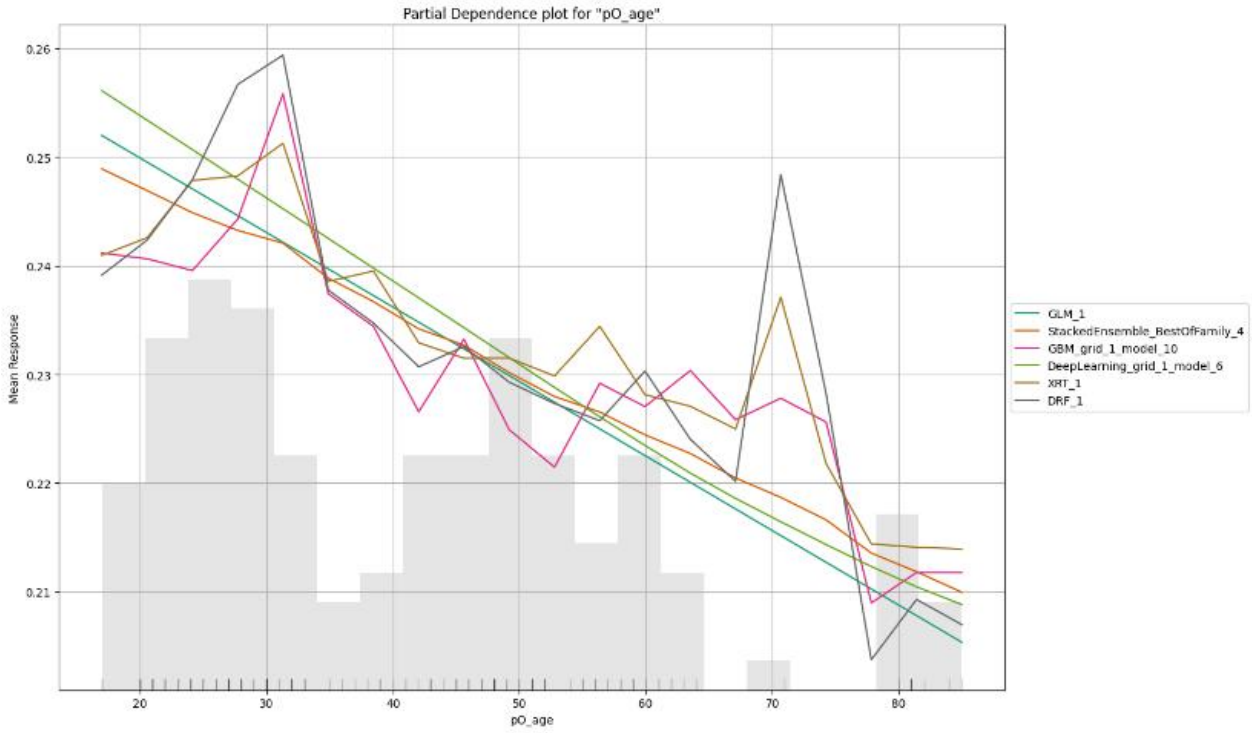


**Figure 21. The effect of age on PCT levels.**

## 4. Discussion

As integral components of the natural world, humans interact with their environment and undergo changes that parallel those occurring in nature. Rooted in the philosophical concept of the unity of Heaven and Man and in ancient scholars' holistic observations of the environment and human health, the traditional Chinese medicine principles of "correspondence between Heaven and Man" and "Unity of Heaven and Man" have informed approaches to disease prevention and treatment. Because both the natural environment and the human internal milieu are constantly changing, "Unity of Heaven and Man" may be understood as a state of dynamic equilibrium. This concept also embodies an ecological perspective of symbiosis. By examining the symbiotic relationship between humans and nature, it highlights the ecological mechanisms underlying this dynamic balance and offers a framework for understanding the interplay between environmental changes and human health (Li et al., 2022; Wang & Xue, 2026).

Air pollutants enter the human body primarily through the respiratory tract, potentially contributing to diseases affecting multiple organ systems and posing a major threat to population health in large and medium-sized cities (Karimi & Samadi, 2024; Nakhjirgan et al., 2023). Against the backdrop of rapid economic development, industrialization, and urbanization in China, environmental pollution has become an increasingly important public health concern. Consequently, investigating the effects of air pollutants on human health and predicting associated trends may contribute to assessments of population health.

Because airborne pollutants enter the body through the nose and mouth, the nasal and pharyngeal mucosae are among the first tissues exposed. The incidence of upper respiratory tract diseases, notably allergic rhinitis and pharyngolaryngeal disorders, may therefore be influenced by air

pollution. Research has demonstrated associations between the atmospheric environment and the incidence of respiratory diseases, with numerous clinical studies focusing on allergic rhinitis (AR). A nationwide cross-sectional study of school-aged children in Taiwan linked AR prevalence to levels of $SO_2$, CO, and $NO_2$ (Huang et al., 2023). Another population-based cross-sectional study in Singapore identified outdoor air pollution as a significant environmental risk factor for AR (Zhang et al., 2025). During 2007–2008, $NO_2$ and $SO_2$ concentrations were associated with increased AR prevalence among kindergarten children in seven cities in Liaoning Province, China (Liu et al., 2014). Moreover, a study from Changsha, China, reported a significant positive correlation between childhood AR prevalence and age-related cumulative exposure to $PM_{10}$, $SO_2$, and $NO_2$ (Lu et al., 2023). Epidemiological studies also suggest that concurrent exposure to allergens and air pollutants may elicit immune responses, including exacerbation of acute respiratory infection symptoms and heightened inflammatory responses characterized by the recruitment of inflammatory cells, cytokines, and interleukins.

Research in China and other countries has also examined the relationship between air pollution and pharyngeal diseases. Particulate pollutants contain heavy metals and microorganisms, and some studies suggest that pollutants can alter the normal structure of the tonsils by affecting their glycosaminoglycan components (Ochoa Scussiatto et al., 2024). Other studies have reported strong associations among chronic pharyngitis, tonsillitis, adenoid hypertrophy, and localized immunoinflammatory reactions induced by air pollution (Chen et al., 2025). Observational research has linked $PM_{2.5}$ exposure to tonsillitis and recurrent acute exacerbations, potentially involving disruption of the throat microbiota by atmospheric pollutants. Air pollution severity may also influence the occurrence of cough. A study examining $PM_{2.5}$ exposure and acute cough in communities in the Pearl River Delta region suggested that short-term increases in community $PM_{2.5}$ exposure elevated the risk of acute cough among local residents (JLee et al., 2025; Wu et al., 2025).

## 5. Conclusion and limitations

Our findings indicate that lymphocyte levels tended to increase with greater exposure to air pollutants, consistent with research examining links between air pollution and upper respiratory tract infections. Increased exposure to various pollutants was also associated with higher eosinophil and basophil levels, broadly consistent with research on air pollution and allergic rhinitis, although confirmation in larger studies is needed. Viewed through the holistic concept of "Unity of Heaven and Man," these findings and the existing literature suggest that air pollution exposure is associated with population health indicators. The results may help inform research on common otorhinolaryngological conditions, including allergic rhinitis, acute and chronic pharyngitis, adenoid hypertrophy, and cough. They also provide a basis for developing and evaluating prevention and treatment strategies for these conditions.

The present study has several limitations. First, fixed-site environmental monitoring data were used as proxies for individual-level exposure to gaseous pollutants. These data may not accurately reflect personal exposure because the distances between participants' residences and monitoring

stations, time–activity patterns, and differences between indoor and outdoor exposure were not accounted for. This may have introduced exposure misclassification and affected the estimated exposure–response relationships. Second, the screening process substantially reduced the sample size, potentially introducing selection bias. This limits the representativeness of the final sample for the population living in the peripheral areas of Beijing and reduces statistical power for subgroup analyses. Third, the cross-sectional study design precludes causal inferences about the temporal relationship between air pollutant exposure and changes in hematological parameters. Furthermore, limited information on participants' baseline health status, including pre-existing diseases and medication use, may have resulted in residual confounding. A single blood test per participant may also have failed to capture within-person variability over time. Future studies should consider individual-level exposure assessments and repeated measurements in longitudinal or panel designs to reduce exposure misclassification and better characterize within-person variation. Collecting more comprehensive covariate data, including socioeconomic status, nutritional factors, and occupational exposures, could also help reduce residual confounding.

**Author Contributions:**

Conceptualization, ZhanfengYan and Xiaoqin Zhou;writing—original draft preparation, Zheng Gong; writing—review and editing, Wenli Wu and Ying Zhang;visualization, Pengyu Li; All author shave read and agreed to the published version of the manuscript.

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**Institutional Review Board Statement:**

The study was reviewed and approved by the Ethics Committee of Dongzhimen Hospital, Beijing University of Chinese Medicine. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki.

**Informed Consent Statement:**

This study was based on the secondary analysis of previously collected data obtained from the National Population Health Data Center Data Repository (PHDA). Informed consent was obtained from all participants or their legal guardians during the original data collection process.

**Data Availability Statement:**

Data utilized in this research were sourced from the National Population Health Data Center Data Repository (PHDA) (http://www.ncmi.cn).

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**Conflict of Interest:**

The authors declare no conflict of interest.

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