DSC 630 Term Project

Christina Vosnak

February 9th, 2025

Impact of Air Quality Metrics and Weather Conditions on Health

In [17]:
```
# Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [2]:
```
# Load data
data = pd.read_csv('air_quality_health_impact_data.csv')
data.head()
```

Out[2]:

	RecordID	AQI	PM10	PM2_5	NO2	SO2	O3	Temp
0	1	187.270059	295.853039	13.038560	6.639263	66.161150	54.624280	5.
1	2	475.357153	246.254703	9.984497	16.318326	90.499523	169.621728	1.
2	3	365.996971	84.443191	23.111340	96.317811	17.875850	9.006794	1.
3	4	299.329242	21.020609	14.273403	81.234403	48.323616	93.161033	21.
4	5	78.009320	16.987667	152.111623	121.235461	90.866167	241.795138	9.

In [3]:
```
# Check Size of the data
data.shape
```

Out[3]:
```
(5811, 15)
```

In [4]:
```
# Check data types for each column
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5811 entries, 0 to 5810
Data columns (total 15 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   RecordID             5811 non-null   int64  
 1   AQI                  5811 non-null   float64
 2   PM10                 5811 non-null   float64
 3   PM2_5                5811 non-null   float64
 4   NO2                  5811 non-null   float64
 5   SO2                  5811 non-null   float64
 6   O3                   5811 non-null   float64
 7   Temperature          5811 non-null   float64
 8   Humidity             5811 non-null   float64
 9   WindSpeed            5811 non-null   float64
 10  RespiratoryCases     5811 non-null   int64  
 11  CardiovascularCases  5811 non-null   int64  
 12  HospitalAdmissions   5811 non-null   int64  
 13  HealthImpactScore    5811 non-null   float64
 14  HealthImpactClass    5811 non-null   float64
dtypes: float64(11), int64(4)
memory usage: 681.1 KB
```

In [5]:

```
# Check for missing values
data.isnull().sum()
```

Out[5]:

```
RecordID               0
AQI                    0
PM10                   0
PM2_5                  0
NO2                    0
SO2                    0
O3                     0
Temperature            0
Humidity               0
WindSpeed              0
RespiratoryCases       0
CardiovascularCases    0
HospitalAdmissions     0
HealthImpactScore      0
HealthImpactClass      0
dtype: int64
```

In [6]:

```
# Check for duplicate values
data.duplicated().sum()
```

Out[6]:

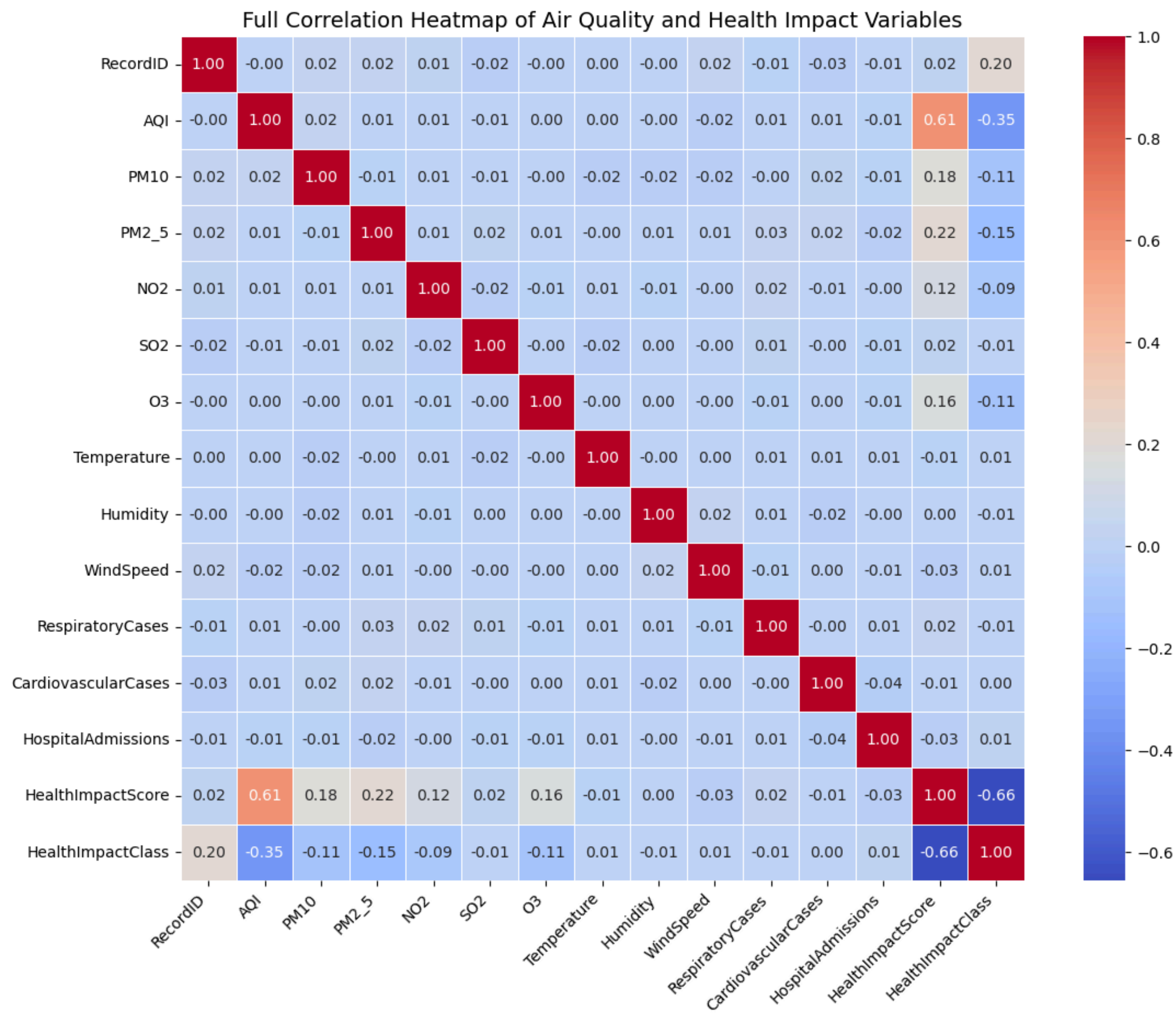
```
0
```

The information above shows that there is no missing data in the dataset.

In [7]:

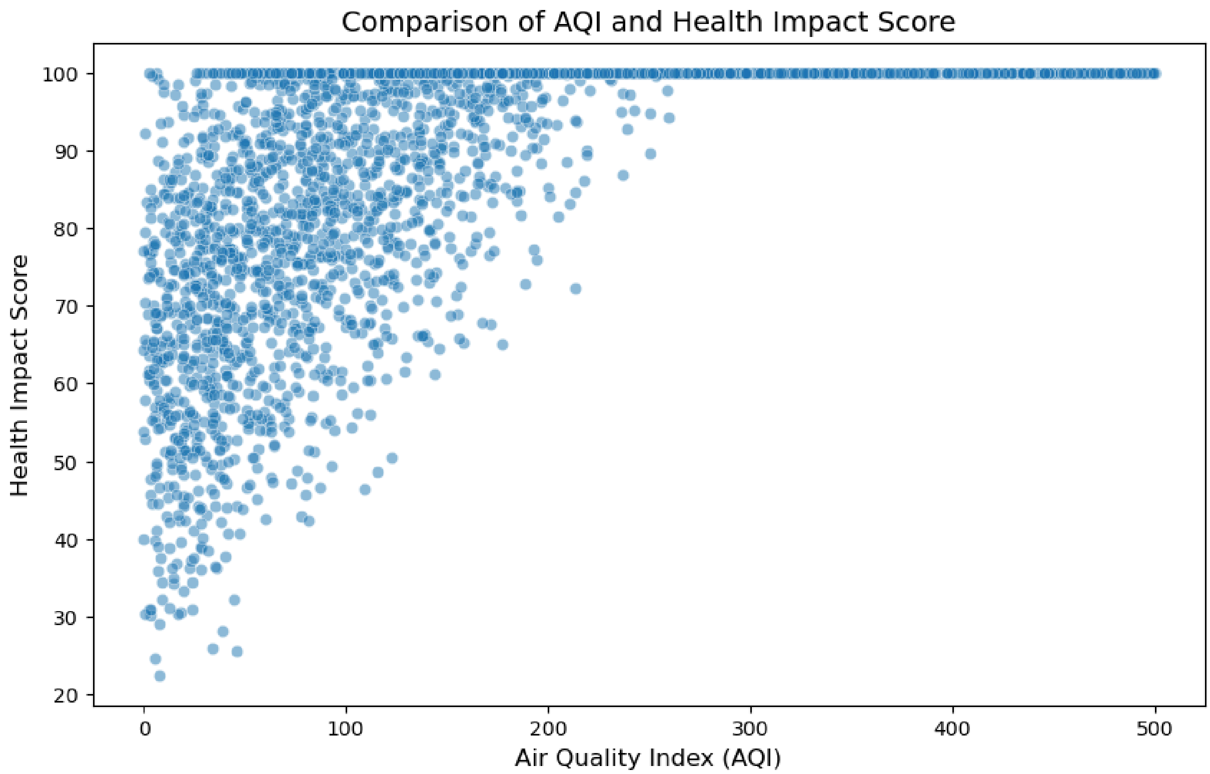
```
# Create Correlation Heatmap to conduct preliminary analysis
plt.figure(figsize=(14, 10))
heatmap = sns.heatmap(data.corr(), annot=True, cmap='coolwarm', fmt=".2f", linewidt

# Improve layout and readability
```

```python
plt.title("Full Correlation Heatmap of Air Quality and Health Impact Variables", fo
plt.xticks(rotation=45, ha="right", fontsize=10)
plt.yticks(fontsize=10)

plt.show()
```

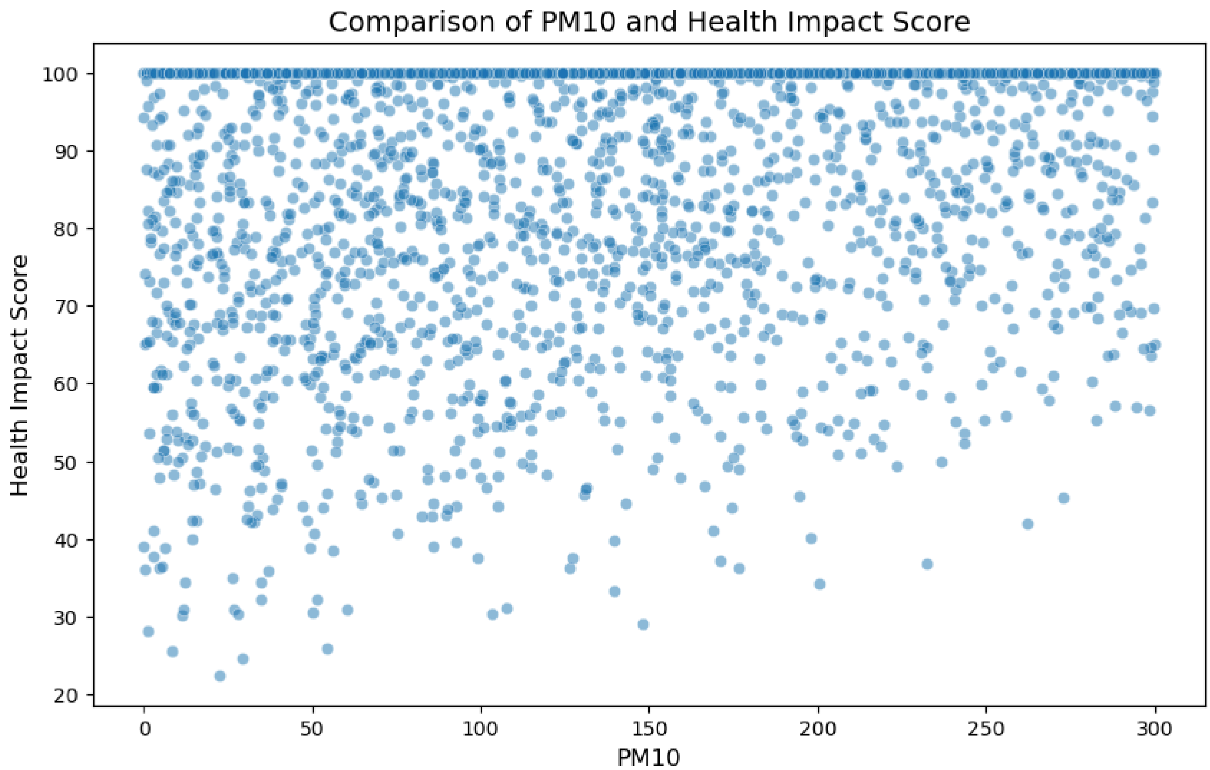


In [8]:

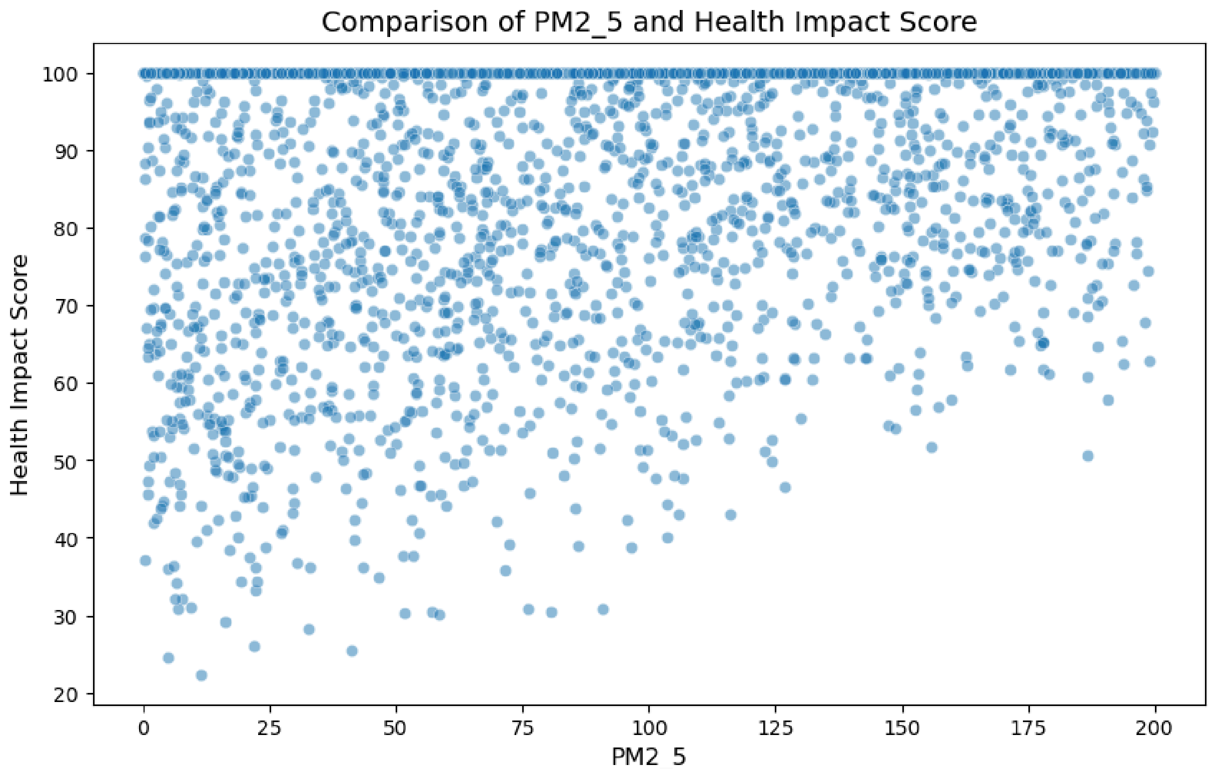
```python
# Create Chart Comparing AQI and Health Impact Score
plt.figure(figsize=(10, 6))

# Scatter plot comparing AQI and Health Impact Score
sns.scatterplot(x=data['AQI'], y=data['HealthImpactScore'], alpha=0.5)

# Titles and labels
plt.title("Comparison of AQI and Health Impact Score", fontsize=14)
plt.xlabel("Air Quality Index (AQI)", fontsize=12)
plt.ylabel("Health Impact Score", fontsize=12)

# Show the plot
plt.show()
```



In [9]:
```
# Create Chart Comparing PM10 and Health Impact Score
plt.figure(figsize=(10, 6))

# Scatter plot comparing AQI and Health Impact Score
sns.scatterplot(x=data['PM10'], y=data['HealthImpactScore'], alpha=0.5)

# Titles and label
plt.title("Comparison of PM10 and Health Impact Score", fontsize=14)
plt.xlabel("PM10", fontsize=12)
plt.ylabel("Health Impact Score", fontsize=12)

# Show the plot
plt.show()
```

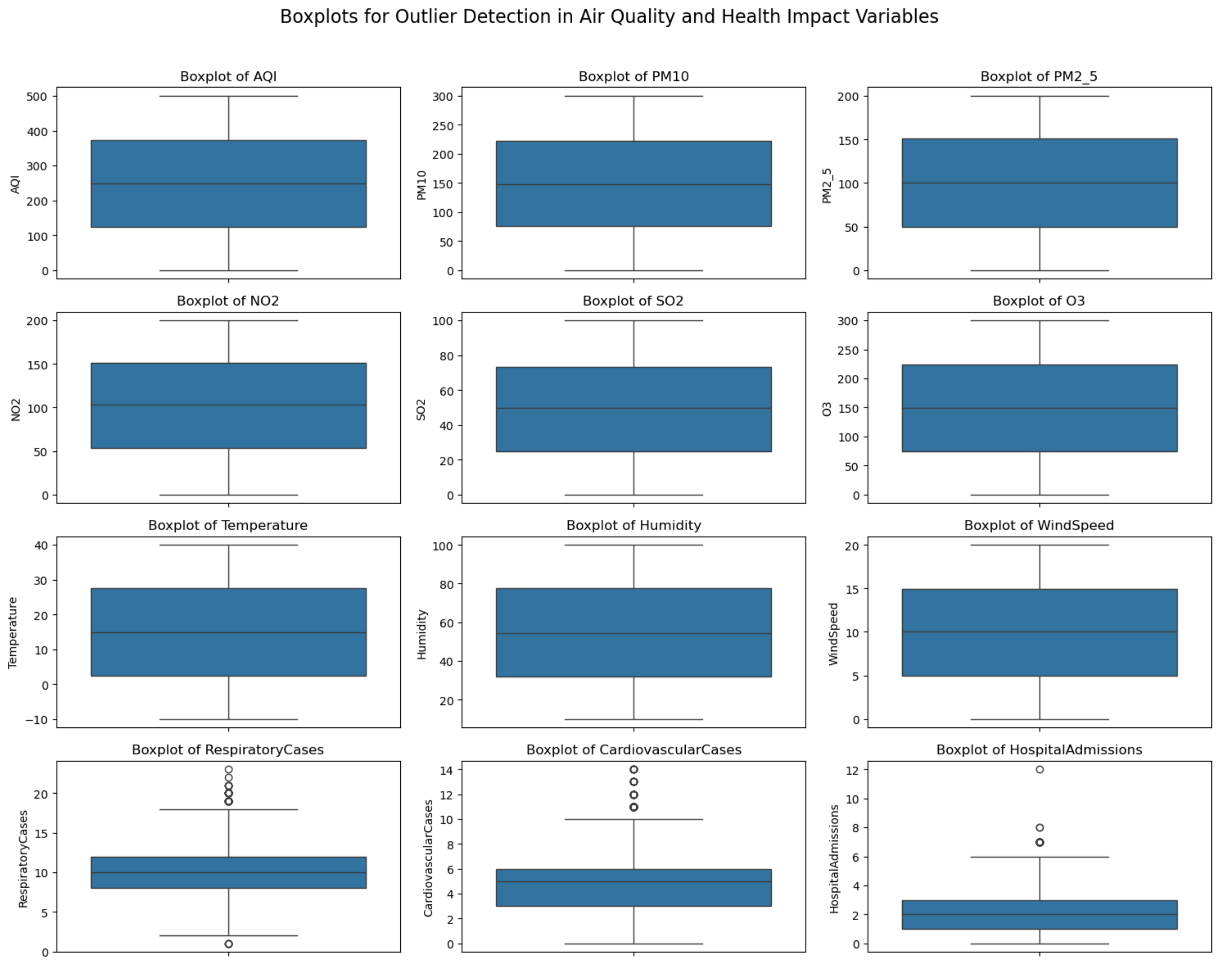


In [10]:
```
# Create Chart Comparing PM2_5 and Health Impact Score
plt.figure(figsize=(10, 6))

# Scatter plot comparing PM2_5 and Health Impact Score
sns.scatterplot(x=data['PM2_5'], y=data['HealthImpactScore'], alpha=0.5)

# Titles and labels
plt.title("Comparison of PM2_5 and Health Impact Score", fontsize=14)
plt.xlabel("PM2_5", fontsize=12)
plt.ylabel("Health Impact Score", fontsize=12)

# Show the plot
plt.show()
```

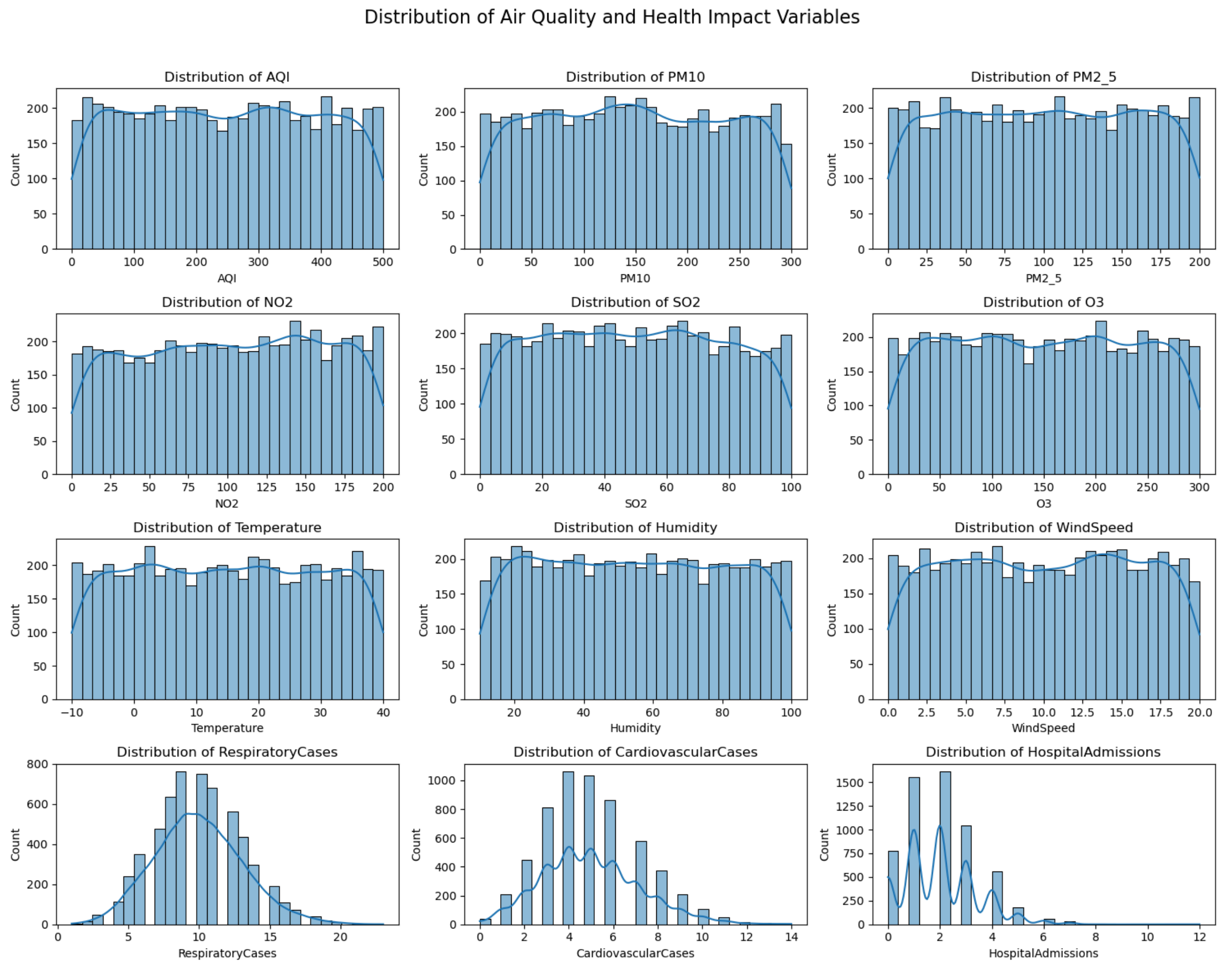


In [11]:

```
# Creating boxplots for outlier detection in key variables
fig, axes = plt.subplots(4, 3, figsize=(15, 12))
fig.suptitle("Boxplots for Outlier Detection in Air Quality and Health Impact Varia

# List of columns to plot
columns_to_plot = ['AQI', 'PM10', 'PM2_5', 'NO2', 'SO2', 'O3', 'Temperature', 'Humi

# Create boxplots for each variable
for ax, col in zip(axes.flatten(), columns_to_plot):
    sns.boxplot(y=data[col], ax=ax)
    ax.set_title(f"Boxplot of {col}")

# Adjust layout for better readability
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```



In [12]:
```
# Creating distribution plots for key air quality and health impact variables
fig, axes = plt.subplots(4, 3, figsize=(15, 12))
fig.suptitle("Distribution of Air Quality and Health Impact Variables", fontsize=16

# List of columns to plot
columns_to_plot = ['AQI', 'PM10', 'PM2_5', 'NO2', 'SO2', 'O3', 'Temperature', 'Humi
# Create distribution plots for each variable
for ax, col in zip(axes.flatten(), columns_to_plot):
    sns.histplot(data[col], bins=30, kde=True, ax=ax)
    ax.set_title(f"Distribution of {col}")

# Adjust layout for better readability
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```



In [13]:

```
# Function to count outliers using IQR
def count_outliers(column, data):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[column][(data[column] < lower_bound) | (data[column] > upper_bo
    return len(outliers)

# Detect outliers for all numerical features
numerical_features = data.select_dtypes(include=['float64', 'int64']).columns
outliers = []
for col in numerical_features:
    outliers.append({
        'Feature': col,
        'Num of outliers': count_outliers(col, data)
    })

# Convert to DataFrame and display
outliers_df = pd.DataFrame(outliers)
print(outliers_df)
```

```
                  Feature  Num of outliers
0                RecordID                0
1                     AQI                0
2                    PM10                0
3                   PM2_5                0
4                     NO2                0
5                     SO2                0
6                      O3                0
7             Temperature                0
8                Humidity                0
9               WindSpeed                0
10       RespiratoryCases               42
11  CardiovascularCases               74
12     HospitalAdmissions               31
13      HealthImpactScore             1352
14      HealthImpactClass             1003
```

In [14]:
```python
# Create Features and Target Variable
X = data.drop(columns=['HealthImpactScore', 'HealthImpactClass'])
y = data['HealthImpactScore']
```

In [18]:
```python
# One-hot encode categorical variables
X = pd.get_dummies(X, drop_first=True)

# Standardize numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [19]:
```python
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, ran
```

In [20]:
```python
lr = LinearRegression()
lr.fit(X_train, y_train)
```

Out[20]:
```
▾ LinearRegression
LinearRegression()
```

In [21]:
```python
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
```

Out[21]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

In [23]:
```python
models = {"Linear Regression": lr, "Random Forest": rf}

for name, model in models.items():
    y_pred = model.predict(X_test)
    print(f"Model: {name}")
    print("MAE:", mean_absolute_error(y_test, y_pred))
    print("MSE:", mean_squared_error(y_test, y_pred))
    print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
```

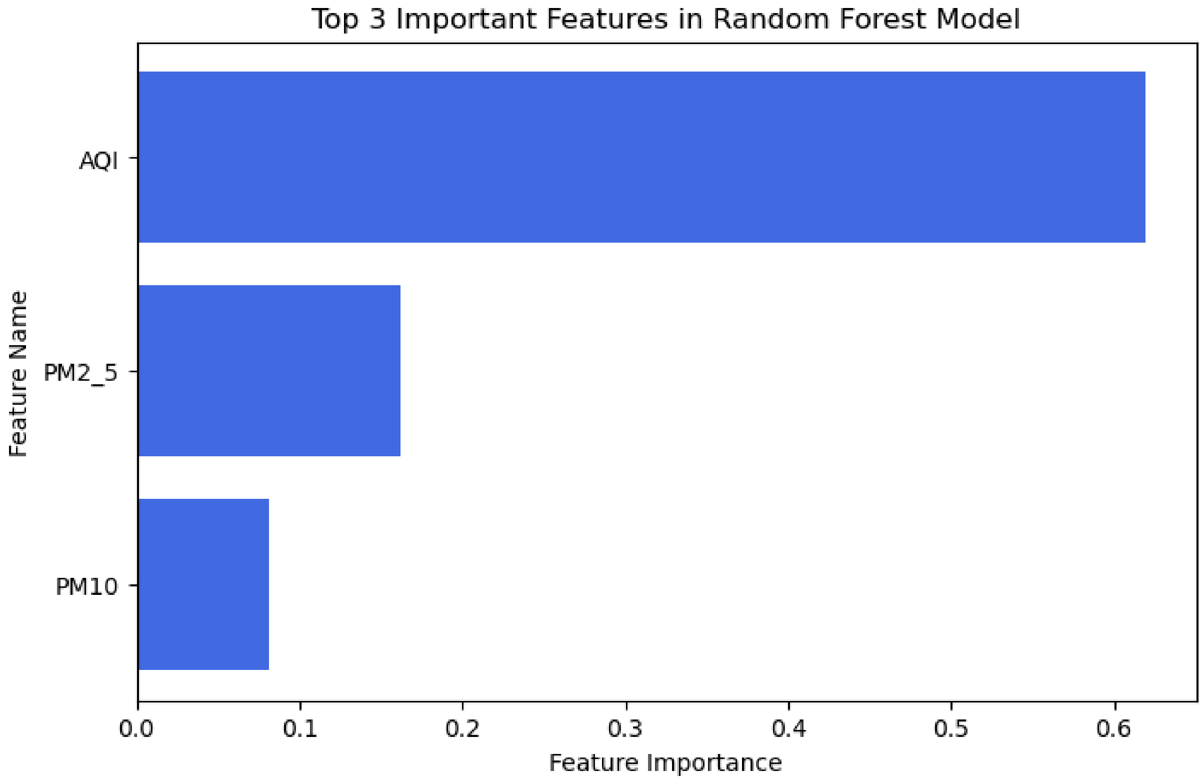
```python
    print("R² Score:", r2_score(y_test, y_pred))
    print("-" * 40)
```

```
Model: Linear Regression
MAE: 7.356775305712758
MSE: 92.6651461558134
RMSE: 9.626273741994531
R² Score: 0.5054324194576925
----------------------------------------
Model: Random Forest
MAE: 1.5758572616603441
MSE: 10.329369986851852
RMSE: 3.213933724713665
R² Score: 0.9448706257438612
----------------------------------------
```

In [24]:

```python
# Extract feature importances from the trained Random Forest model
feature_importances = rf.feature_importances_

# Create a DataFrame to pair feature names with their importance scores
feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': feature_importances
})

# Sort features by importance in descending order
top_features = feature_importance_df.sort_values(by="Importance", ascending=False).

# Display the top 3 features
print(top_features)

# Plot the top 3 features
plt.figure(figsize=(8, 5))
plt.barh(top_features["Feature"], top_features["Importance"], color="royalblue")
plt.xlabel("Feature Importance")
plt.ylabel("Feature Name")
plt.title("Top 3 Important Features in Random Forest Model")
plt.gca().invert_yaxis()  # Invert y-axis for better visualization
plt.show()
```

```
  Feature  Importance
1     AQI    0.619246
3   PM2_5    0.161854
2    PM10    0.080753
```


Top 3 Important Features in Random Forest Model
AQI
PM2_5
PM10
Feature Name
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Feature Importance

In [ ]: