Step 1: Importing Libraries and Loading Data

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from scipy.stats import pearsonr
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from sklearn.metrics import r2_score, mean_squared_error
```

```
df = pd.read_csv('Train.csv')
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 26 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Gender                        3000 non-null   object
 1   Height (cm)                   3000 non-null   float64
 2   Weight (kg)                   3000 non-null   float64
 3   Blood Pressure (s/d)          3000 non-null   object
 4   Cholesterol Level (mg/dL)     3000 non-null   float64
 5   BMI                           3000 non-null   float64
 6   Blood Glucose Level (mg/dL)   3000 non-null   float64
 7   Bone Density (g/cm²)          3000 non-null   float64
 8   Vision Sharpness              3000 non-null   float64
 9   Hearing Ability (dB)          3000 non-null   float64
 10  Physical Activity Level       3000 non-null   object
 11  Smoking Status                3000 non-null   object
 12  Alcohol Consumption           1799 non-null   object
 13  Diet                          3000 non-null   object
 14  Chronic Diseases              1701 non-null   object
 15  Medication Use                1802 non-null   object
 16  Family History                1549 non-null   object
 17  Cognitive Function            3000 non-null   float64
 18  Mental Health Status          3000 non-null   object
 19  Sleep Patterns                3000 non-null   object
 20  Stress Levels                 3000 non-null   float64
 21  Pollution Exposure            3000 non-null   float64
```

```
 22  Sun Exposure                3000 non-null   float64
 23  Education Level             2373 non-null   object
 24  Income Level                3000 non-null   object
 25  Age (years)                 3000 non-null   int64
dtypes: float64(12), int64(1), object(13)
memory usage: 609.5+ KB
None
```

```
print (df.shape)
```

```
(3000, 26)
```

```
df.head()
```

	Gender	Height (cm)	Weight (kg)	Blood Pressure (s/d)	Cholesterol Level (mg/dL)	BMI	Blood Glucose Level (mg/dL)	B Dens (g/c
0	Male	171.148359	86.185197	151/109	259.465814	29.423017	157.652848	0.132
1	Male	172.946206	79.641937	134/112	263.630292	26.626847	118.507805	0.629
2	Female	155.945488	49.167058	160/101	207.846206	20.217553	143.587550	0.473
3	Female	169.078298	56.017921	133/94	253.283779	19.595270	137.448581	1.184
4	Female	163.758355	73.966304	170/106	236.119899	27.582078	145.328695	0.434

5 rows × 26 columns

Step 2: Data Cleaning and Pre-Processing

```
# Display the count of null values for each column
print(df.isnull().sum())
```

```
Gender                          0
Height (cm)                     0
Weight (kg)                     0
Blood Pressure (s/d)            0
Cholesterol Level (mg/dL)       0
BMI                             0
Blood Glucose Level (mg/dL)     0
Bone Density (g/cm²)            0
Vision Sharpness                0
Hearing Ability (dB)            0
Physical Activity Level         0
Smoking Status                  0
Alcohol Consumption          1201
Diet                            0
Chronic Diseases             1299
Medication Use               1198
Family History               1451
```

```
Cognitive Function            0
Mental Health Status          0
Sleep Patterns                0
Stress Levels                 0
Pollution Exposure            0
Sun Exposure                  0
Education Level             627
Income Level                  0
Age (years)                   0
dtype: int64
```

```
#Minimum values
min_vals = df.min(numeric_only=True)

#Maximum values
max_vals = df.max(numeric_only=True)

#Combine into one DataFrame
min_max_df = pd.DataFrame({'Min': min_vals, 'Max': max_vals})
min_max_df
```

	Min	Max
Height (cm)	141.130985	198.112215
Weight (kg)	32.537672	123.598603
Cholesterol Level (mg/dL)	148.811514	331.300589
BMI	12.049900	43.329869
Blood Glucose Level (mg/dL)	69.866884	185.736144
Bone Density (g/cm²)	-0.219787	1.999829
Vision Sharpness	0.200000	1.062537
Hearing Ability (dB)	0.000000	94.003824
Cognitive Function	30.382098	106.479831
Stress Levels	1.000428	9.996323
Pollution Exposure	0.006395	9.998090
Sun Exposure	0.002055	11.992504
Age (years)	18.000000	89.000000

Next steps: Generate code with min_max_df View recommended plots New interactive sheet

```
#Splitting Blood Pressure s/d into Systolic and Diastolic
df[['Systolic_BP', 'Diastolic_BP']] = df['Blood Pressure (s/d)'].str.split('/', e
df['Systolic_BP'] = pd.to_numeric(df['Systolic_BP'], errors='coerce')
df['Diastolic_BP'] = pd.to_numeric(df['Diastolic_BP'], errors='coerce')

data = df.drop('Blood Pressure (s/d)', axis=1)
```

```
missing_values = data.isnull().sum()
print("\nMissing values per column:\n", missing_values)
```

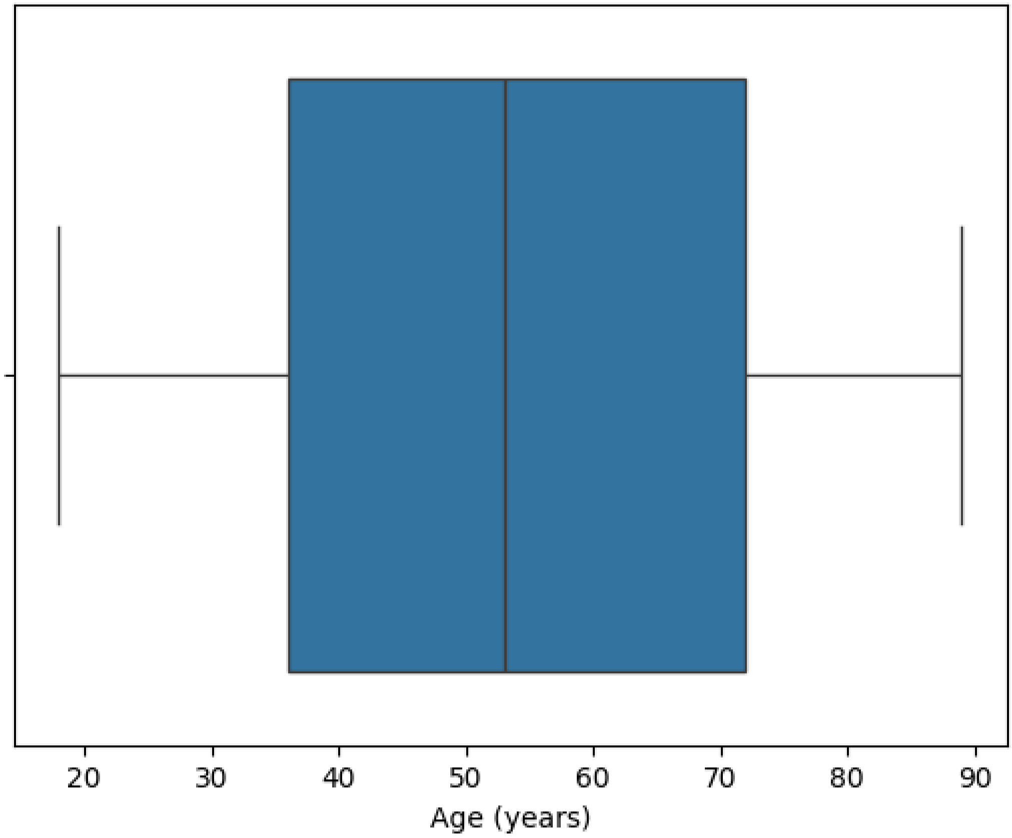
```
Missing values per column:
 Gender                          0
Height (cm)                    0
Weight (kg)                    0
Cholesterol Level (mg/dL)      0
BMI                            0
Blood Glucose Level (mg/dL)    0
Bone Density (g/cm²)           0
Vision Sharpness               0
Hearing Ability (dB)           0
Physical Activity Level        0
Smoking Status                 0
Alcohol Consumption         1201
Diet                           0
Chronic Diseases            1299
Medication Use              1198
Family History              1451
Cognitive Function             0
Mental Health Status           0
Sleep Patterns                 0
Stress Levels                  0
Pollution Exposure             0
Sun Exposure                   0
Education Level              627
Income Level                   0
Age (years)                    0
Systolic_BP                    0
Diastolic_BP                   0
dtype: int64
```

```
#Assigning all numerical variables

numerical_features = ('Height (cm)', 'Weight (kg)', 'Cholesterol Level (mg/dL)',
       'Blood Glucose Level (mg/dL)', 'Bone Density (g/cm²)',
       'Vision Sharpness', 'Hearing Ability (dB)', 'Cognitive Function',
       'Stress Levels', 'Pollution Exposure', 'Sun Exposure', 'Age (years)',
       'Systolic_BP', 'Diastolic_BP')
```

Exploratory Data Analysis

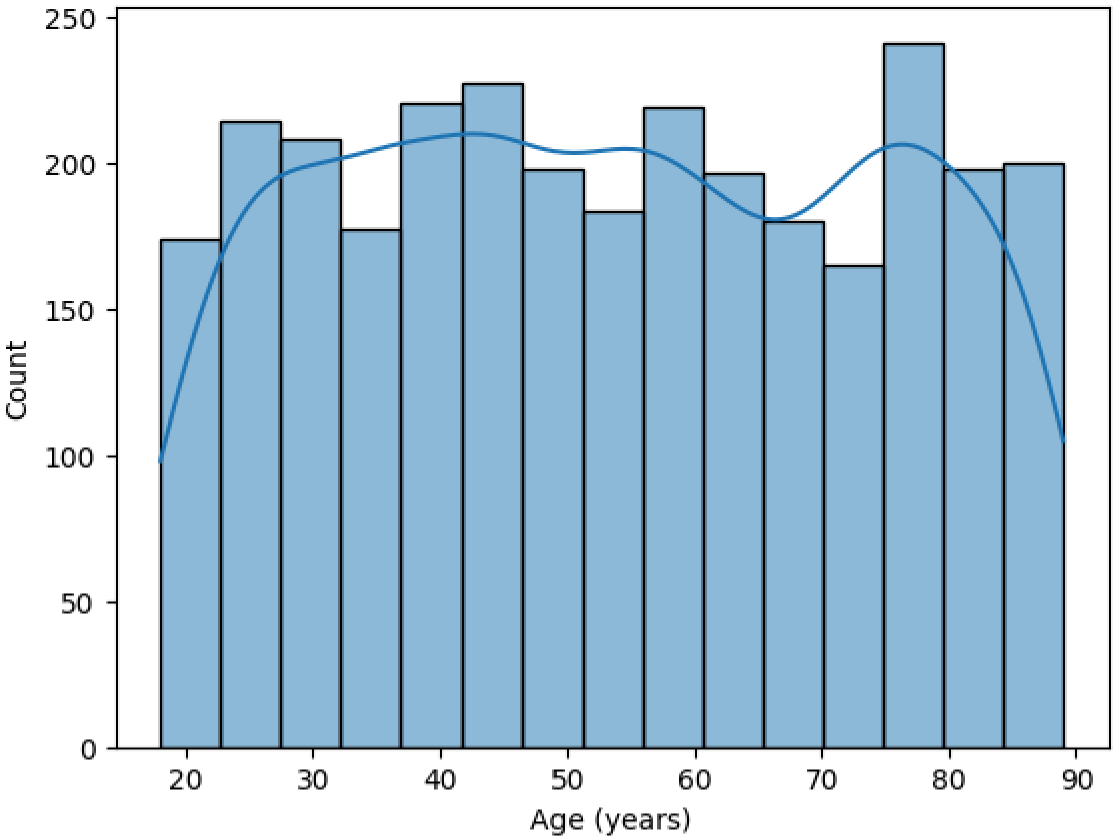
```
#Detecting outliers
sns.boxplot(x=df['Age (years)'])
```

```
<Axes: xlabel='Age (years)'>
```

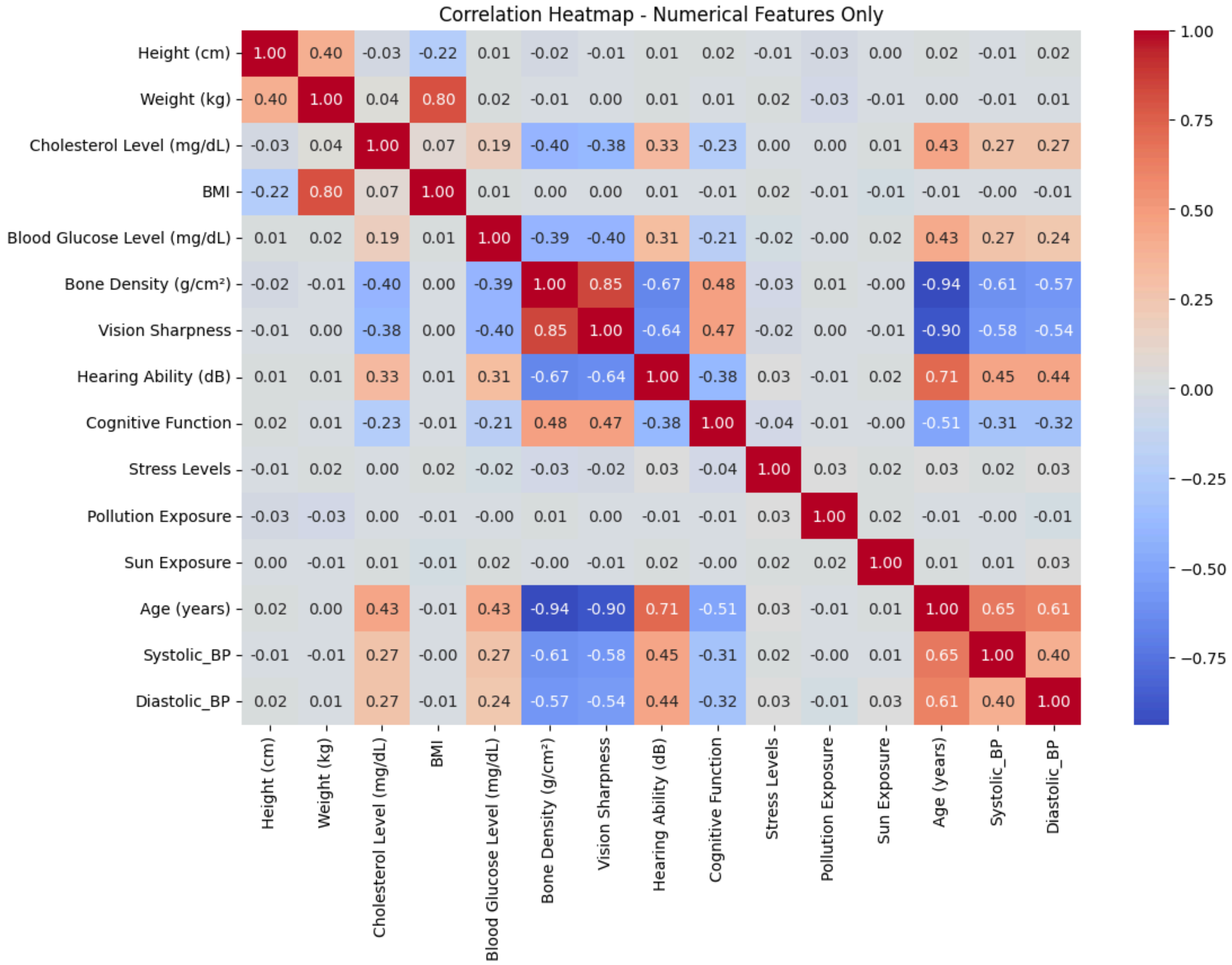



```
#EDA: Distribution of Target Variable
sns.histplot(df['Age (years)'], kde=True)
```

```
<Axes: xlabel='Age (years)', ylabel='Count'>
```

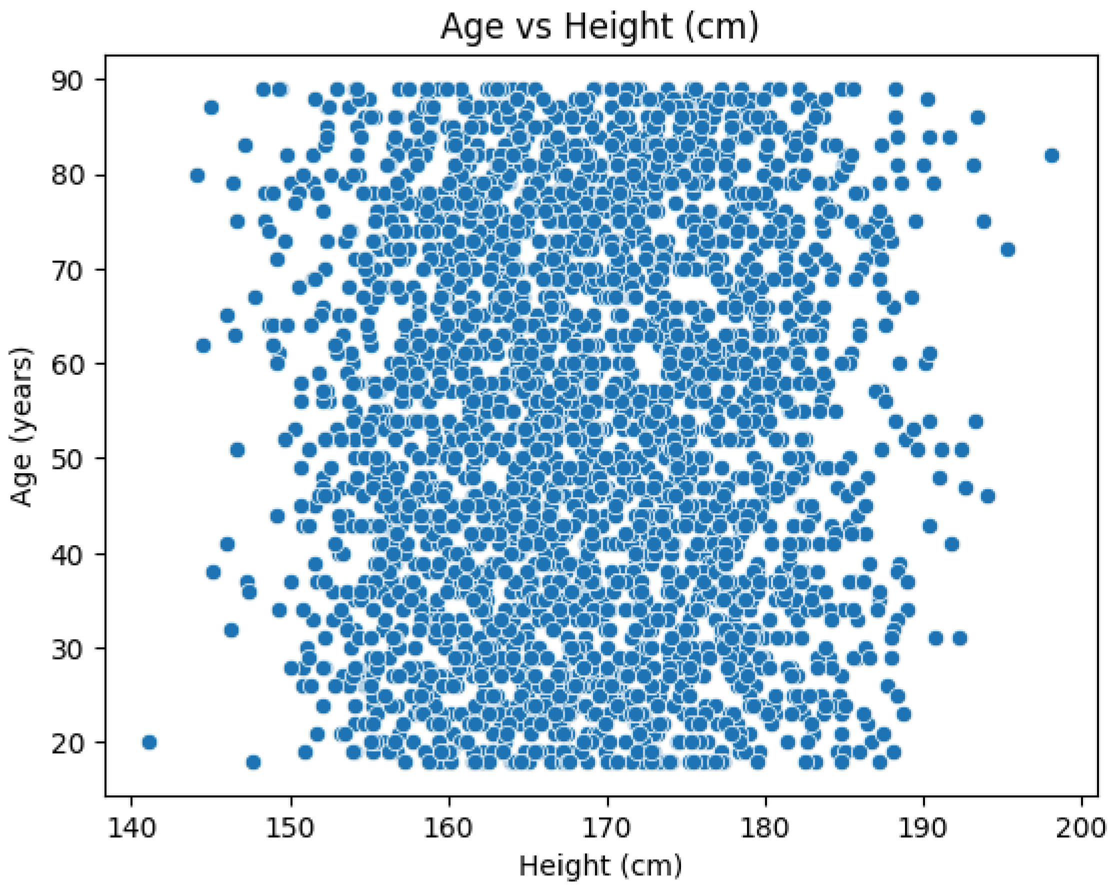


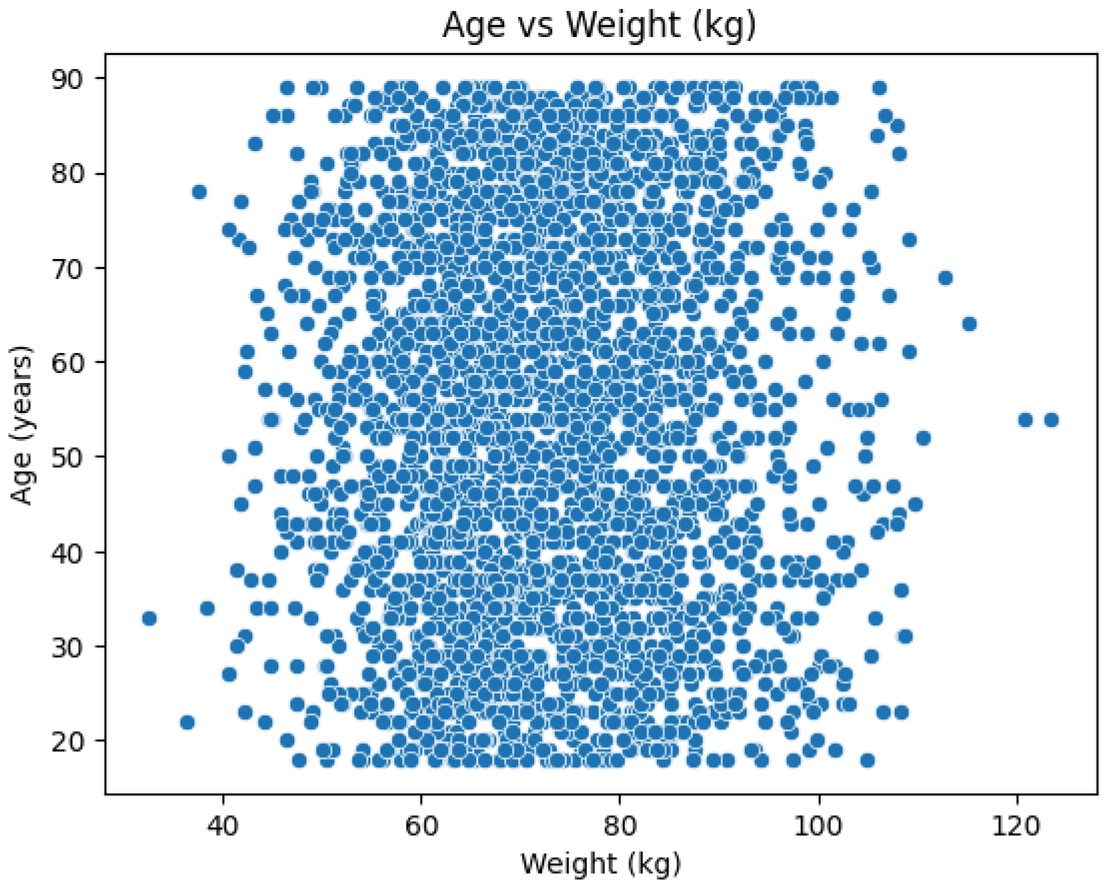
```
plt.figure(figsize=(12, 8))
sns.heatmap(df[list(numerical_features)].corr(), annot=True, cmap='coolwarm', fmt
plt.title("Correlation Heatmap - Numerical Features Only")
plt.show()
```

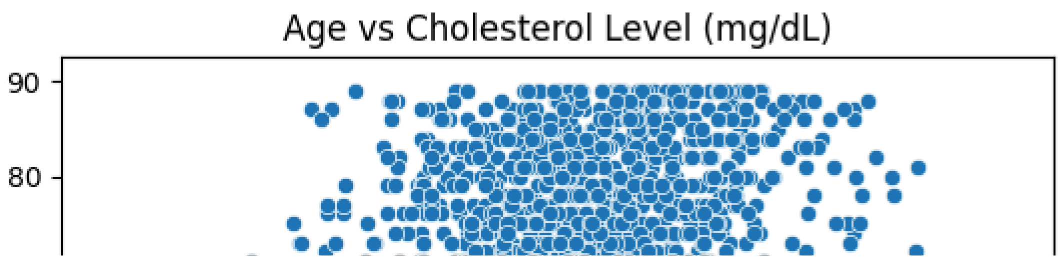


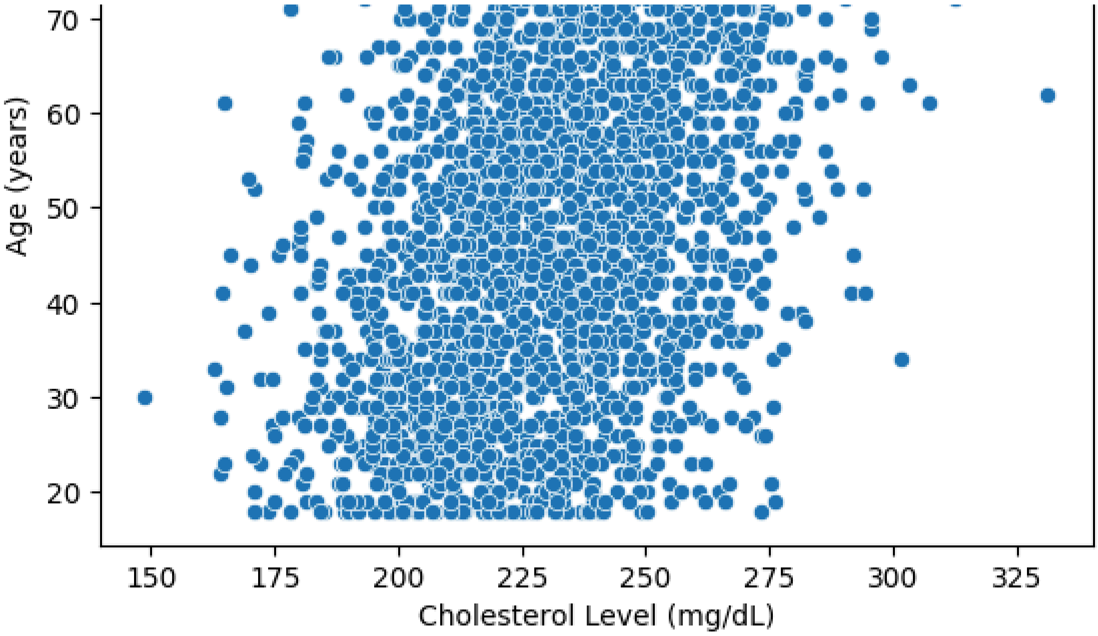

```
#Age v/s Numerical Variables
for col in numerical_features:
    if col != 'Age (years)':  # No indentation here
```

```
    sns.scatterplot(x=col, y='Age (years)', data=df)
    plt.title(f'Age vs {col}')
    plt.show()
```

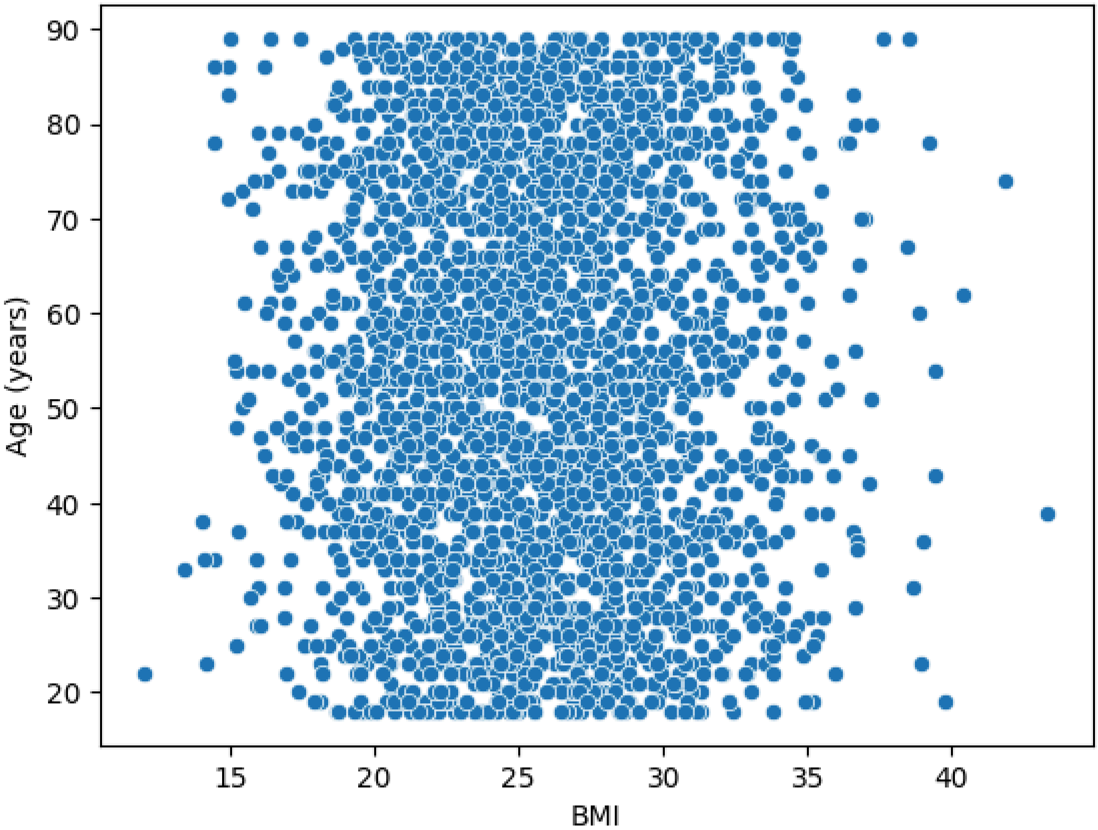

Age vs Height (cm)
Age (years)
Height (cm)
90
80
70
60
50
40
30
20
140
150
160
170
180
190
200


Age vs Weight (kg)
Age (years)
Weight (kg)
90
80
70
60
50
40
30
20
40
60
80
100
120

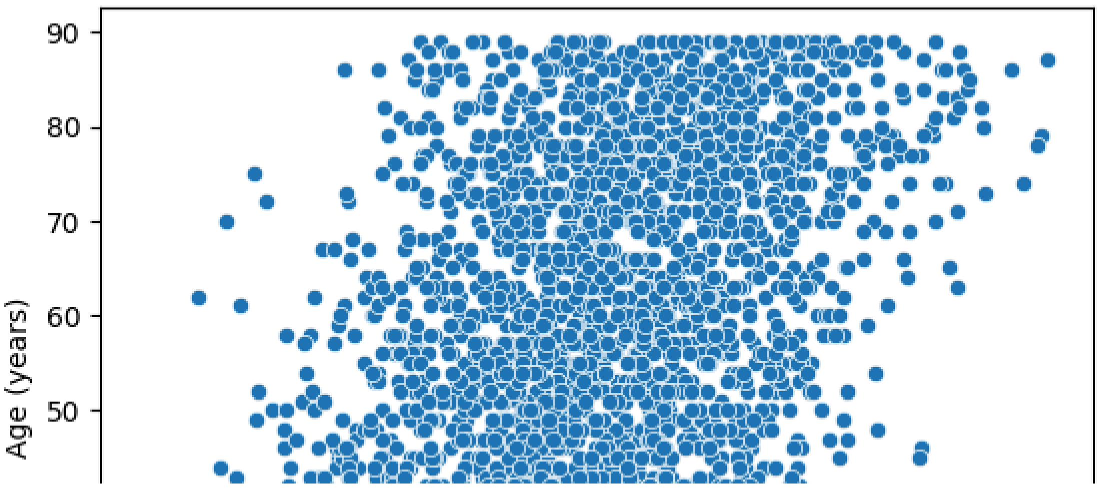

Age vs Cholesterol Level (mg/dL)
90
80

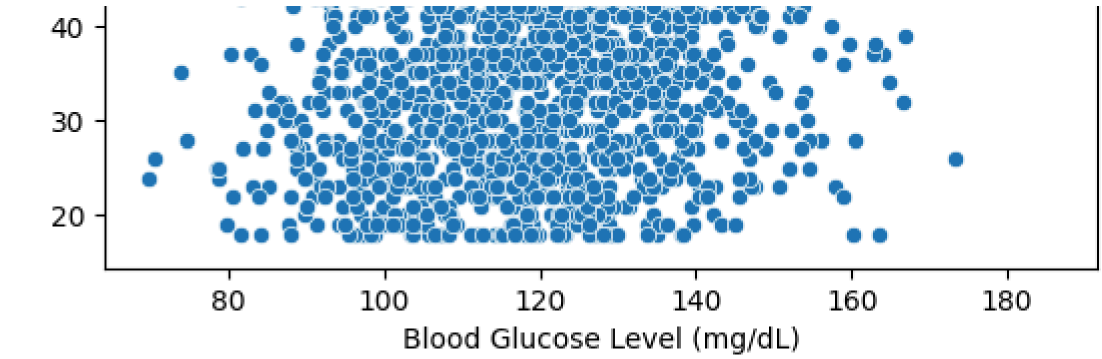


Age vs BMI

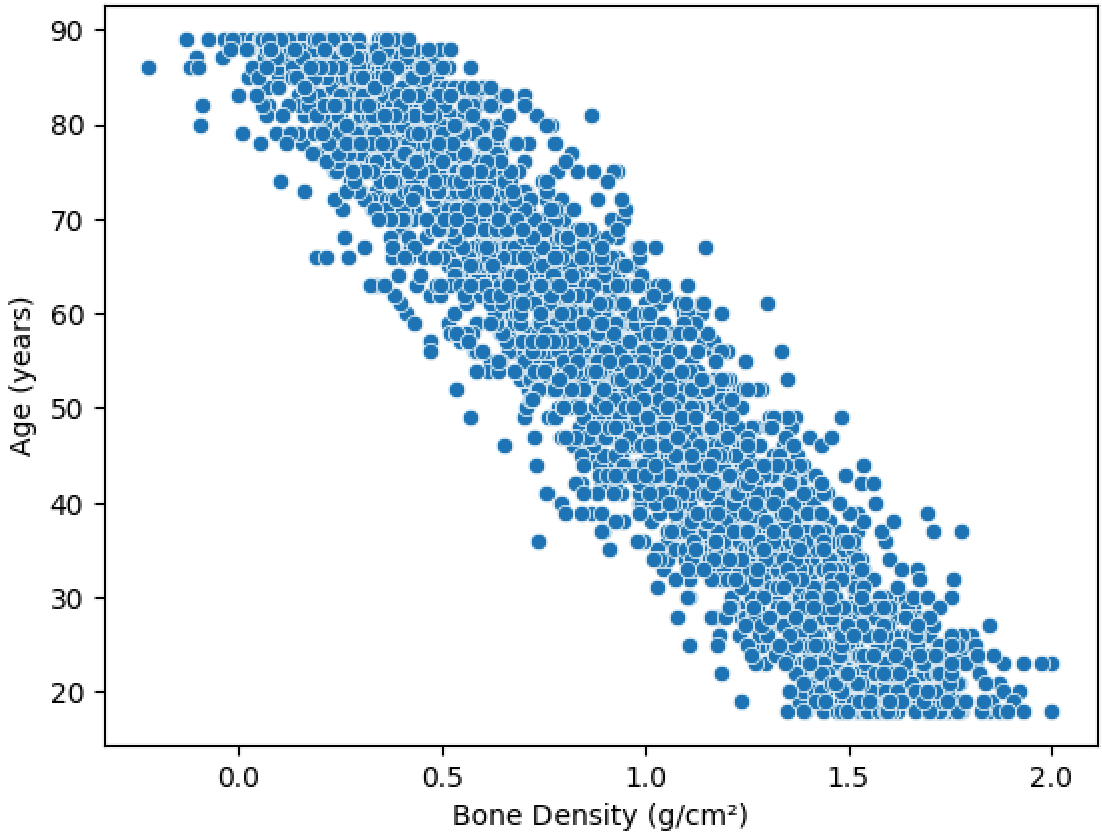


Age vs Blood Glucose Level (mg/dL)

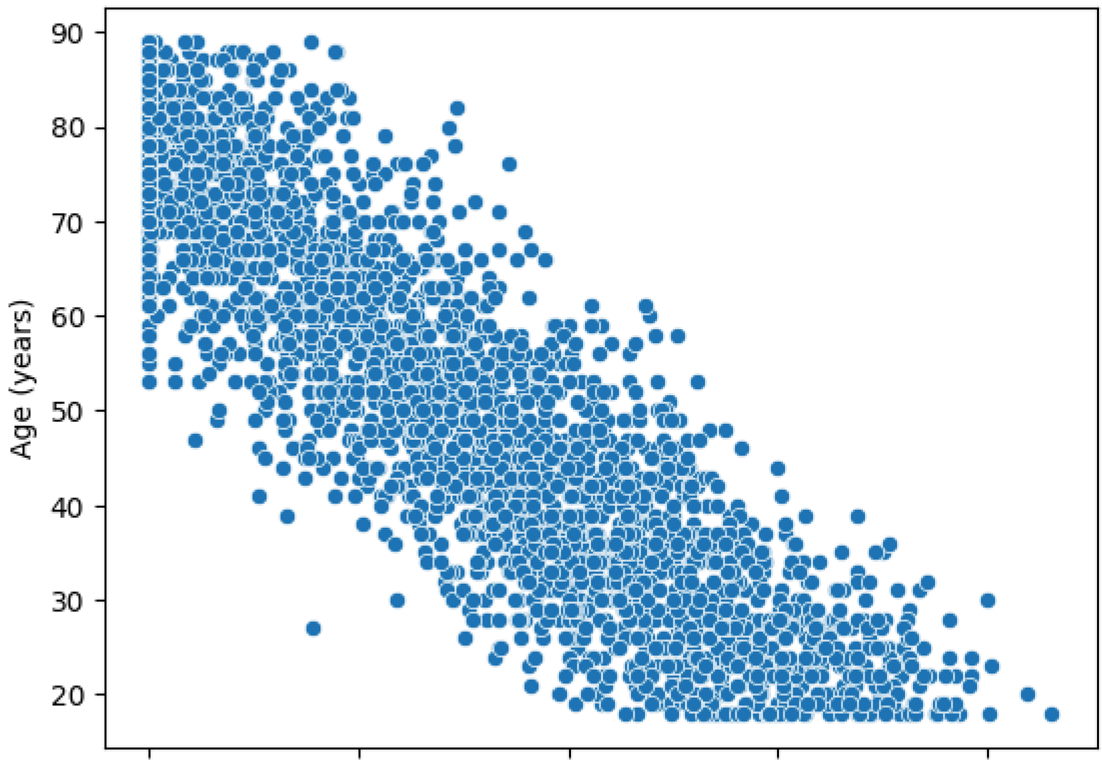


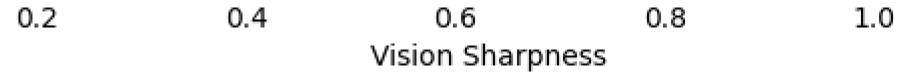


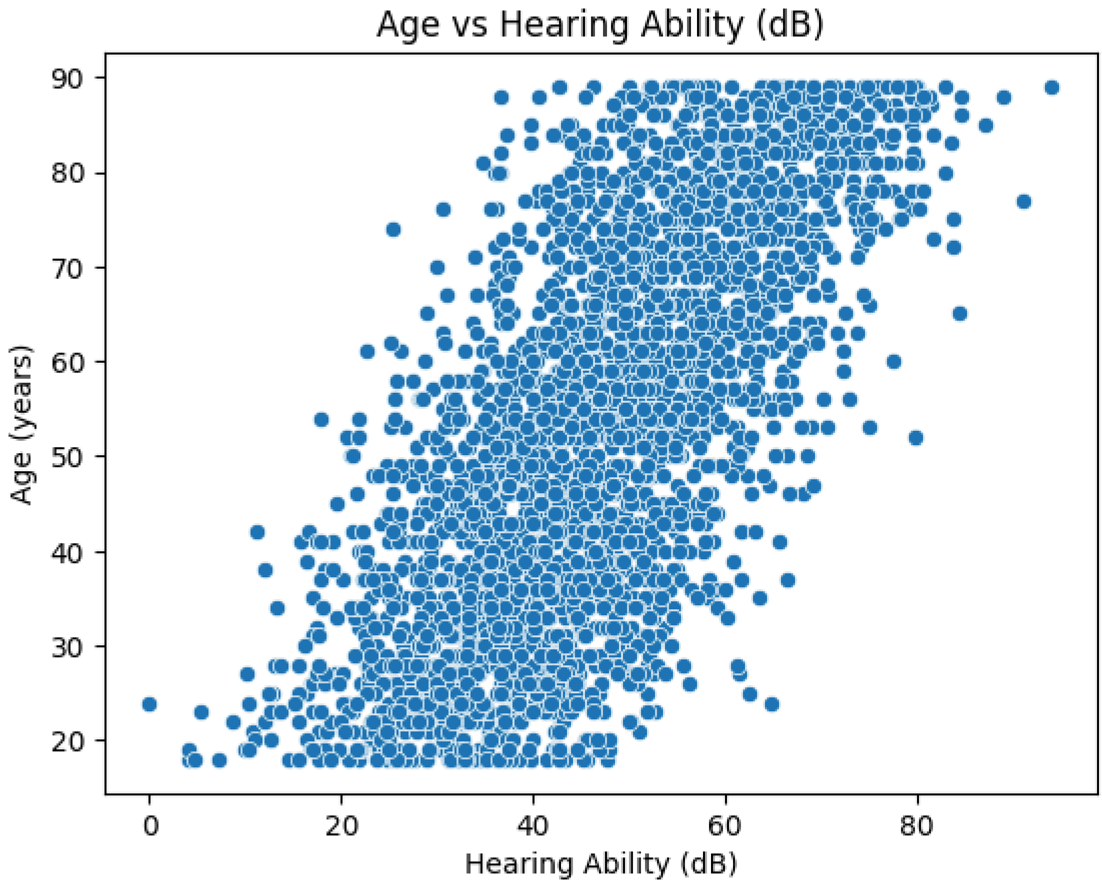
Age vs Bone Density (g/cm^2)

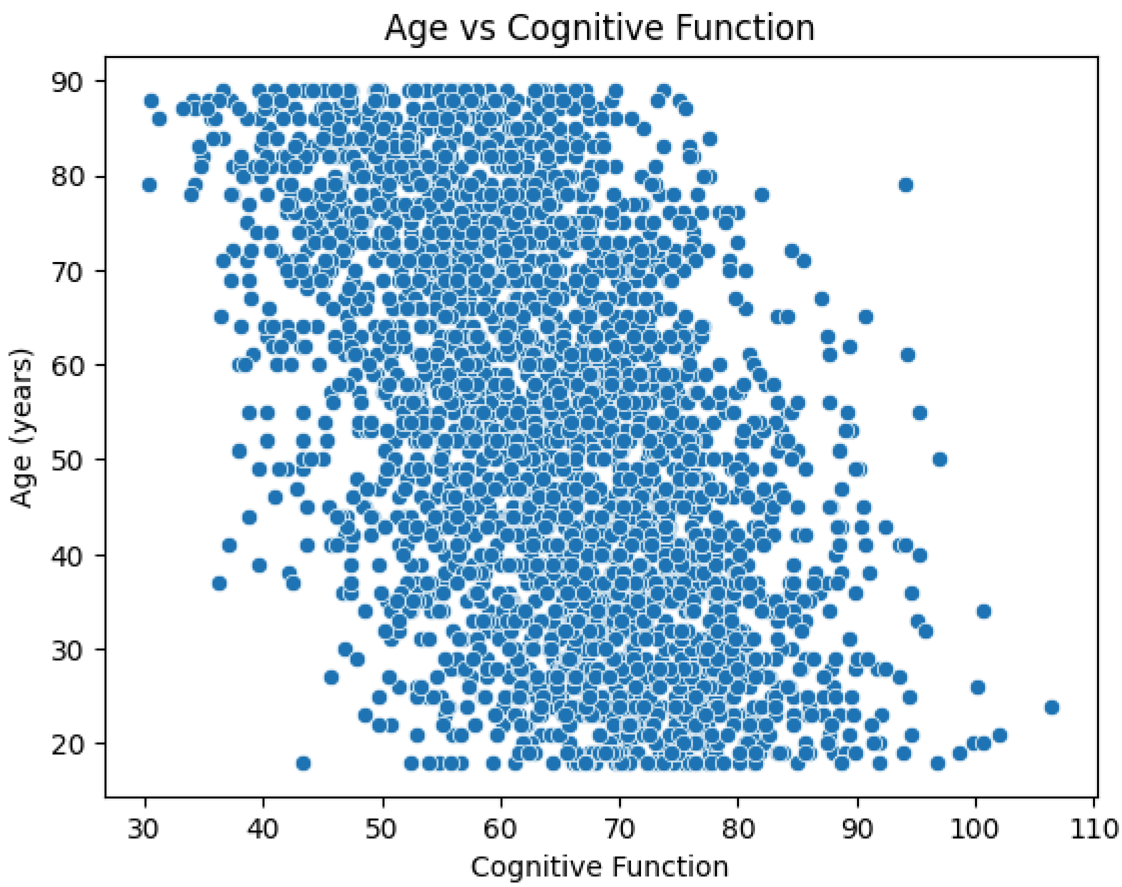


Age vs Vision Sharpness

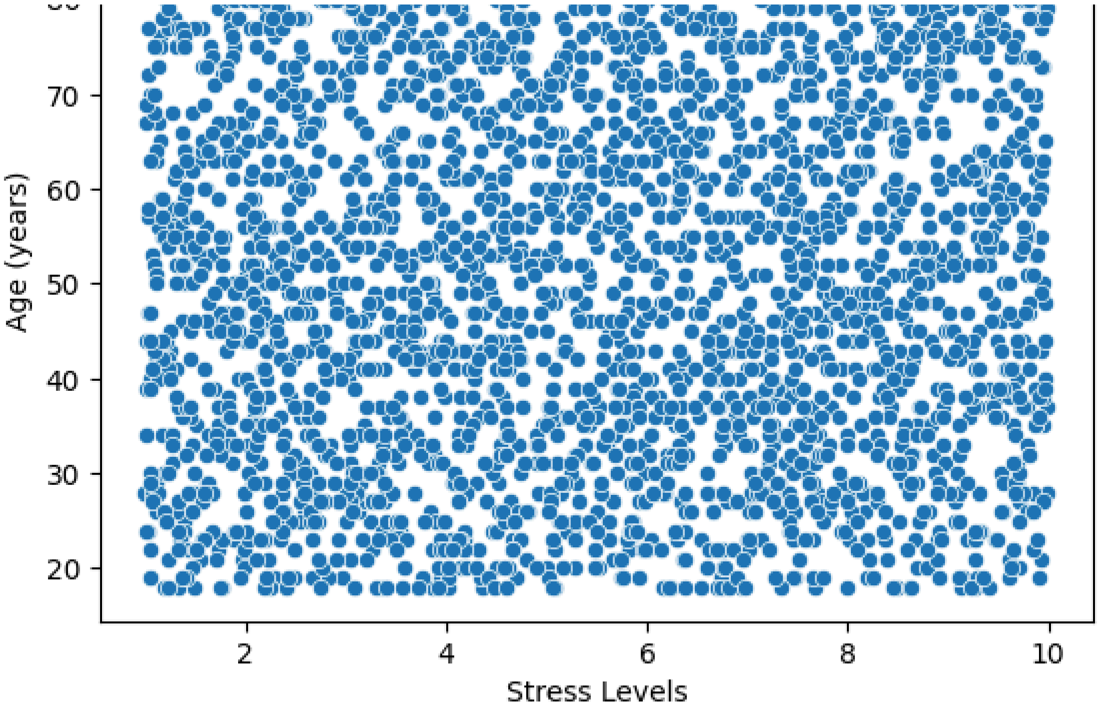


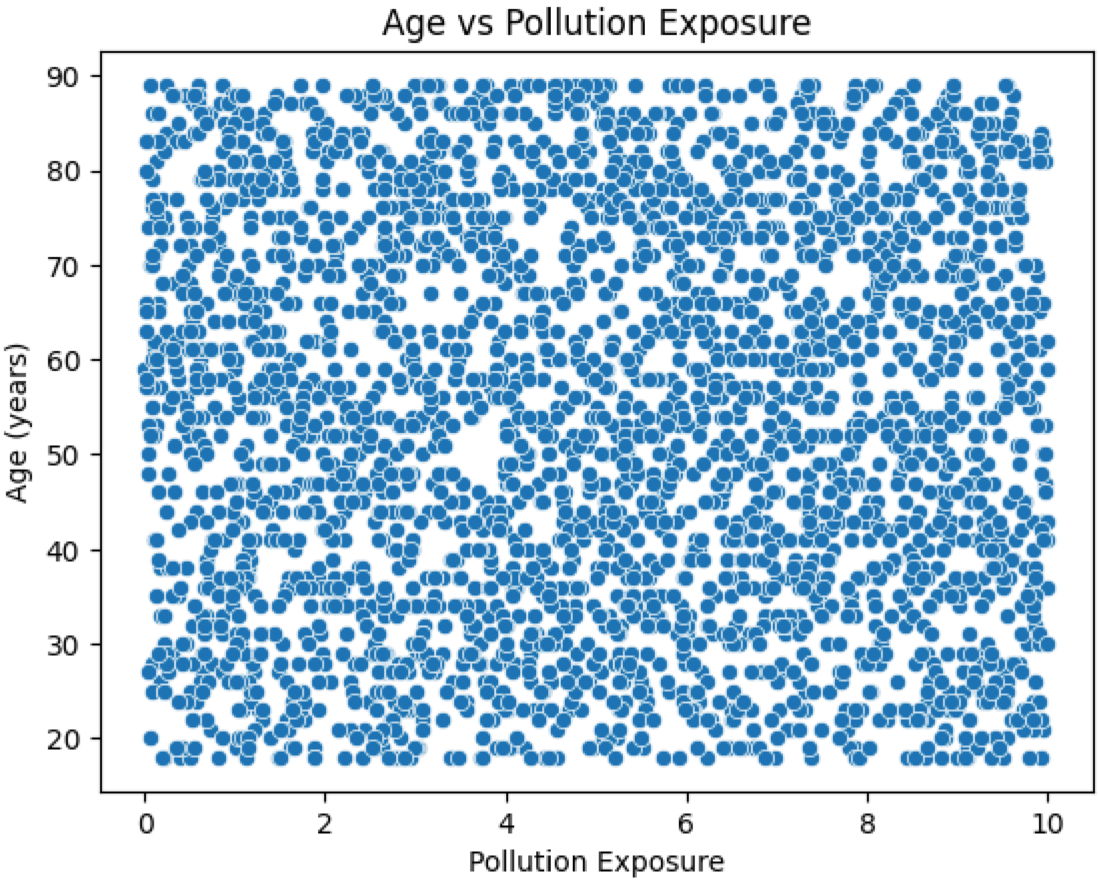

0.2
0.4
0.6
0.8
1.0
Vision Sharpness

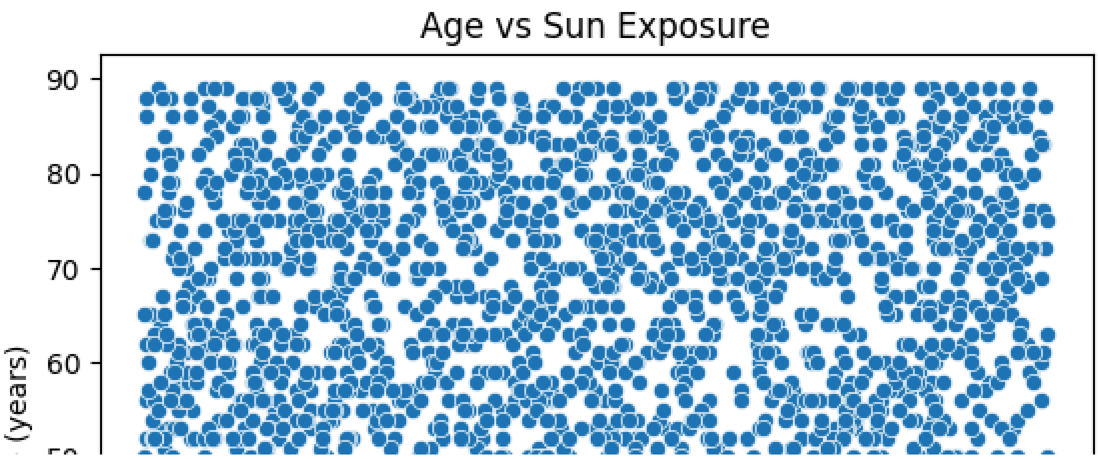

Age vs Hearing Ability (dB)
90
80
70
60
50
40
30
20
Age (years)
0
20
40
60
80
Hearing Ability (dB)

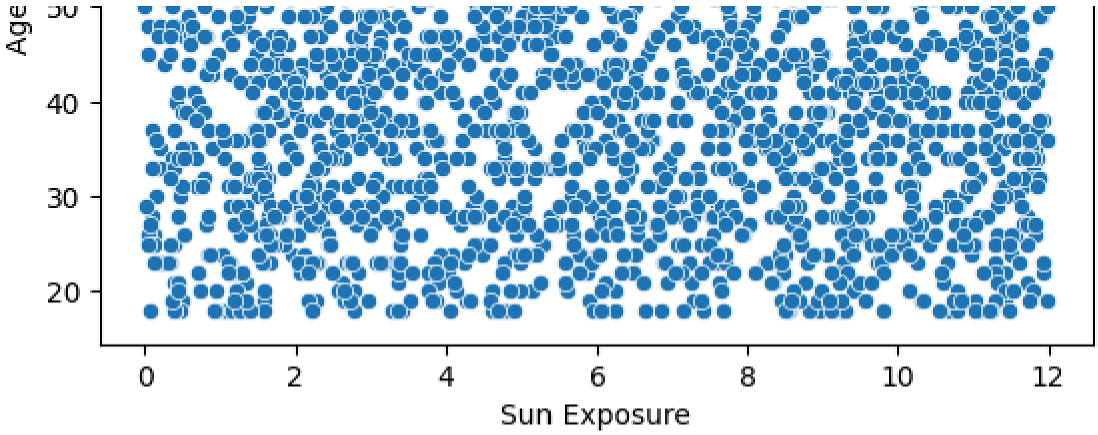

Age vs Cognitive Function
90
80
70
60
50
40
30
20
Age (years)
30
40
50
60
70
80
90
100
110
Cognitive Function

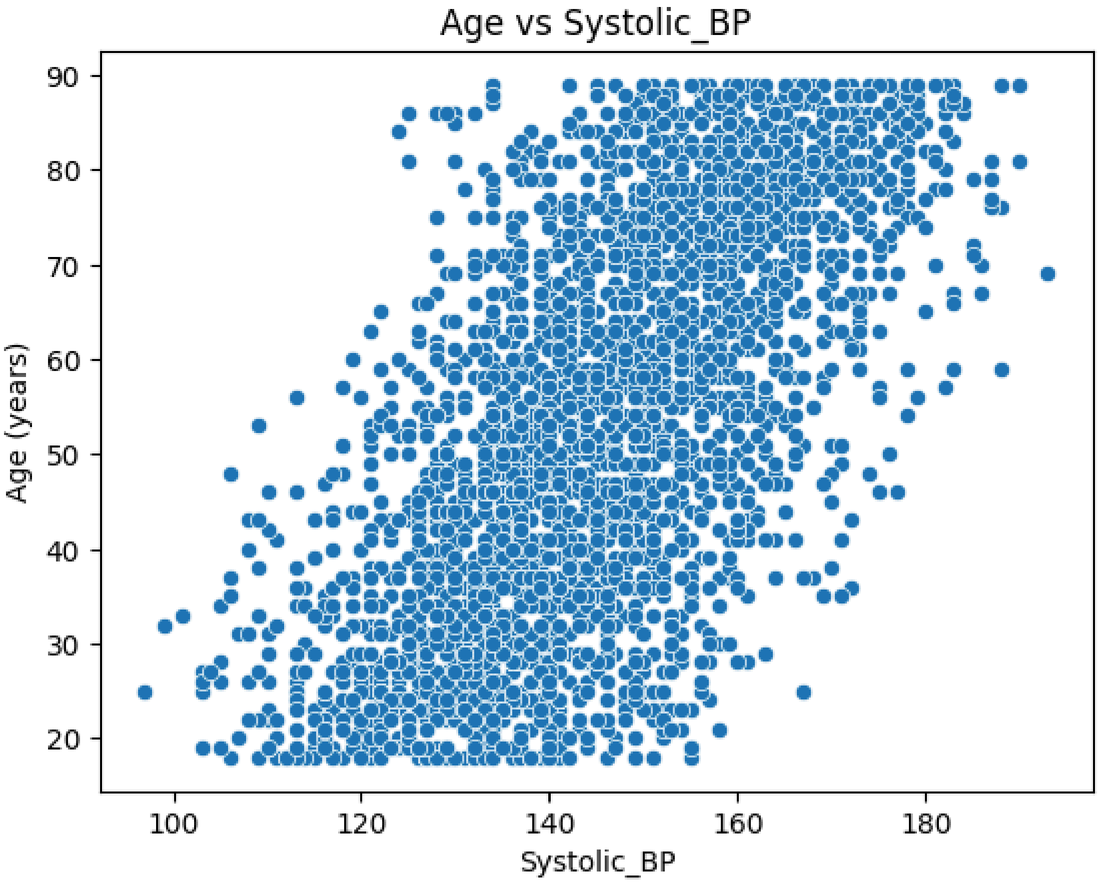

Age vs Stress Levels
90
80

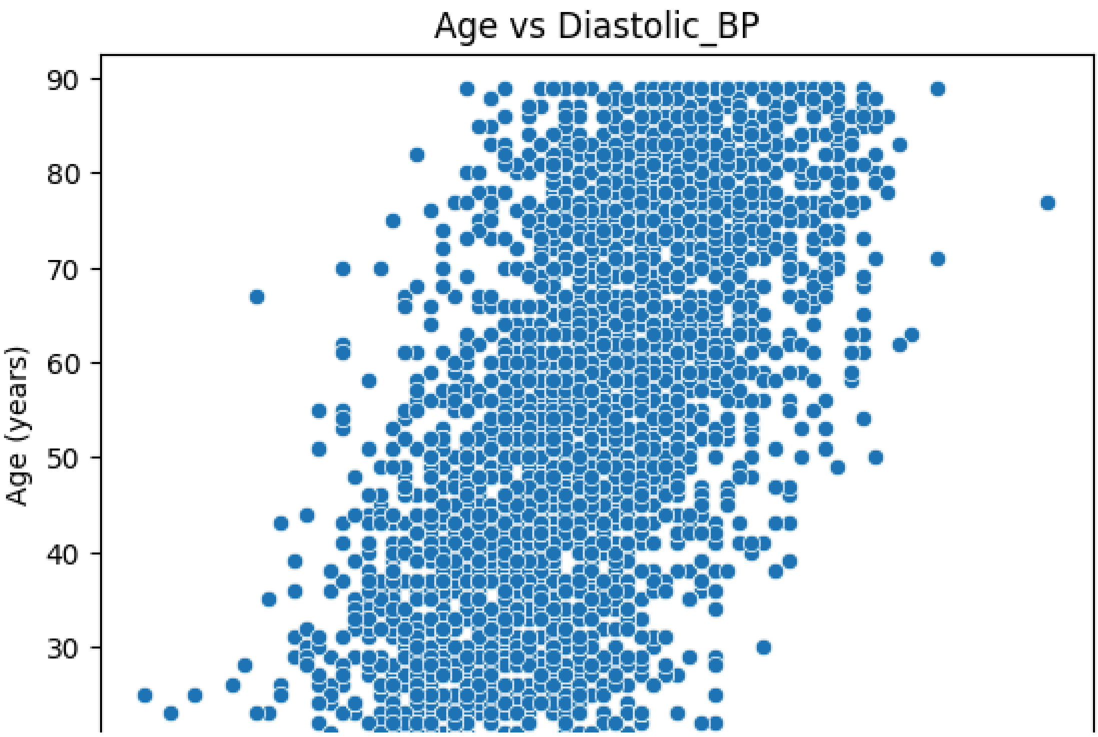

Age (years)
70
60
50
40
30
20
2
4
6
8
10
Stress Levels

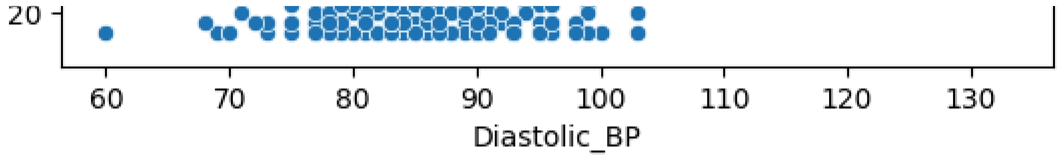

Age vs Pollution Exposure
Age (years)
90
80
70
60
50
40
30
20
0
2
4
6
8
10
Pollution Exposure


Age vs Sun Exposure
(years)
90
80
70
60

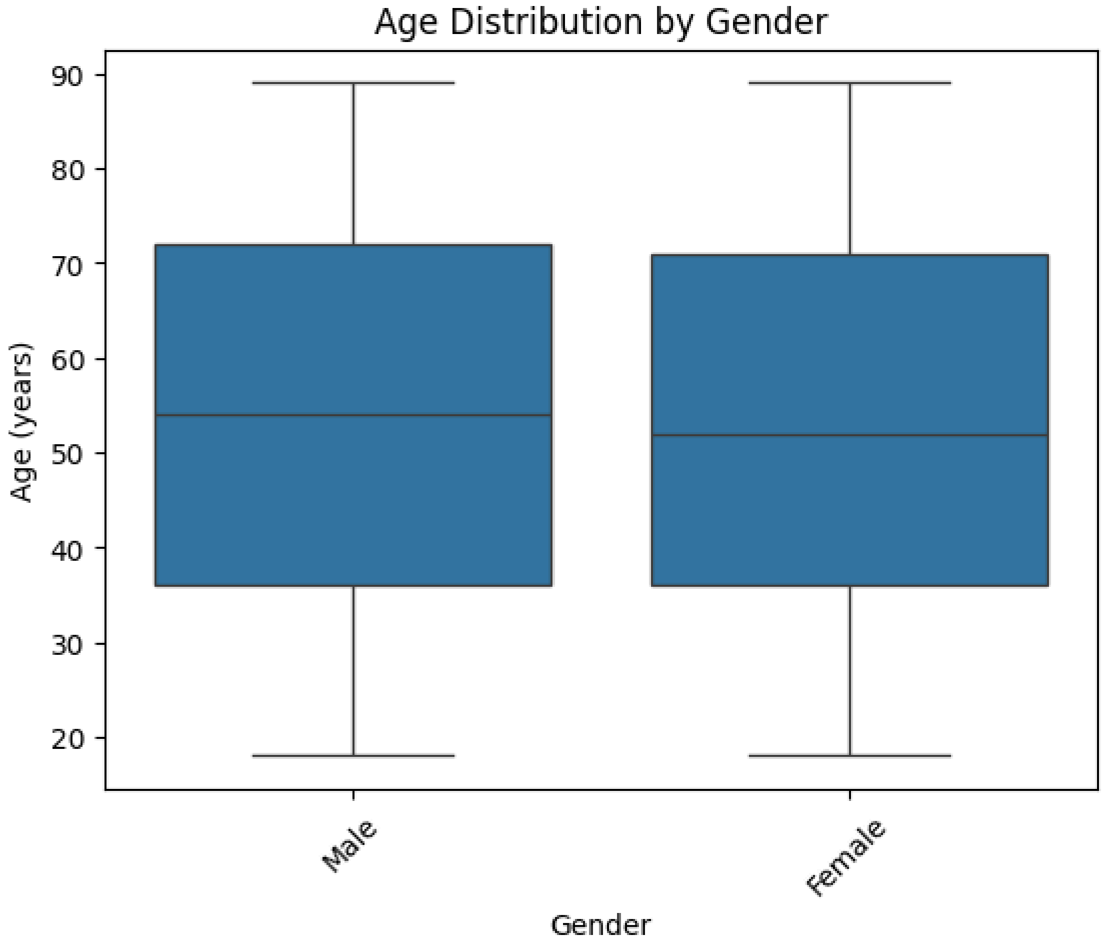

Age
50
40
30
20
0
2
4
6
8
10
12
Sun Exposure

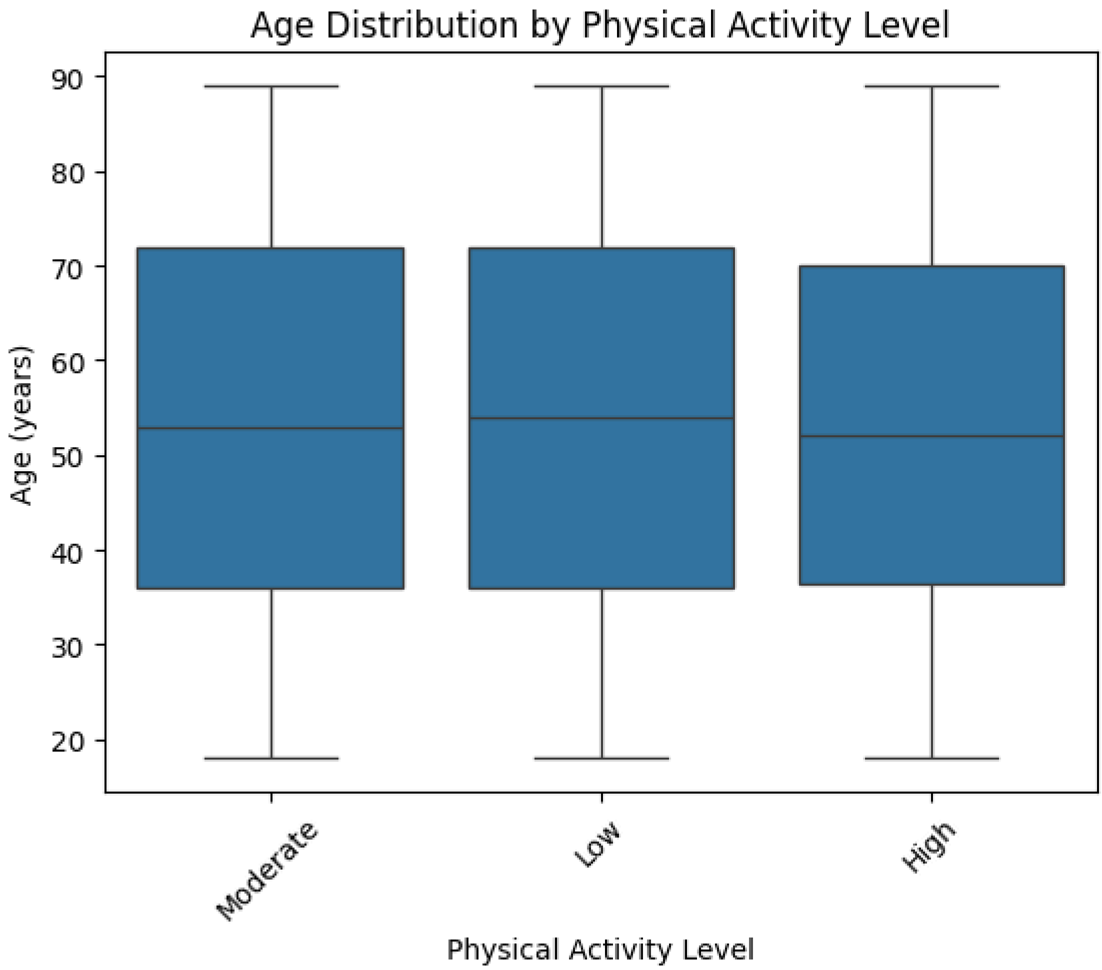

Age vs Systolic_BP
Age (years)
90
80
70
60
50
40
30
20
100
120
140
160
180
Systolic_BP


Age vs Diastolic_BP
Age (years)
90
80
70
60
50
40
30

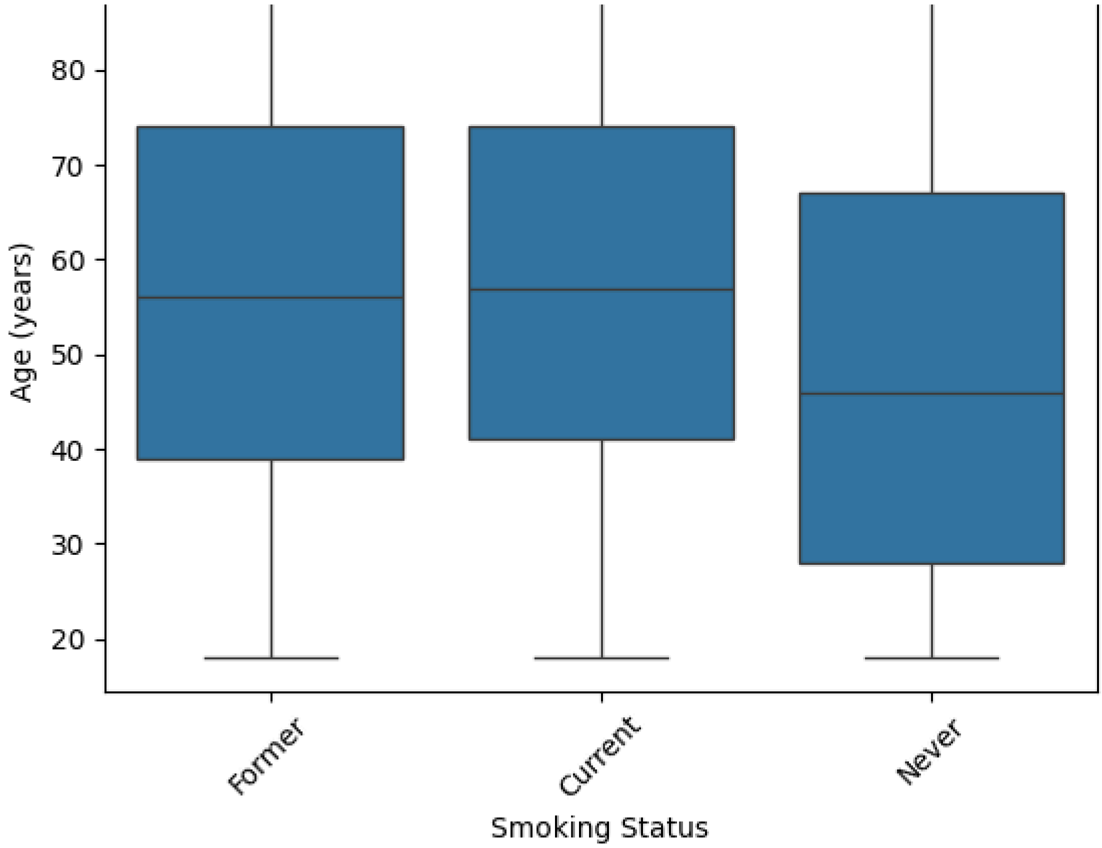

20
60
70
80
90
100
110
120
130
Diastolic_BP

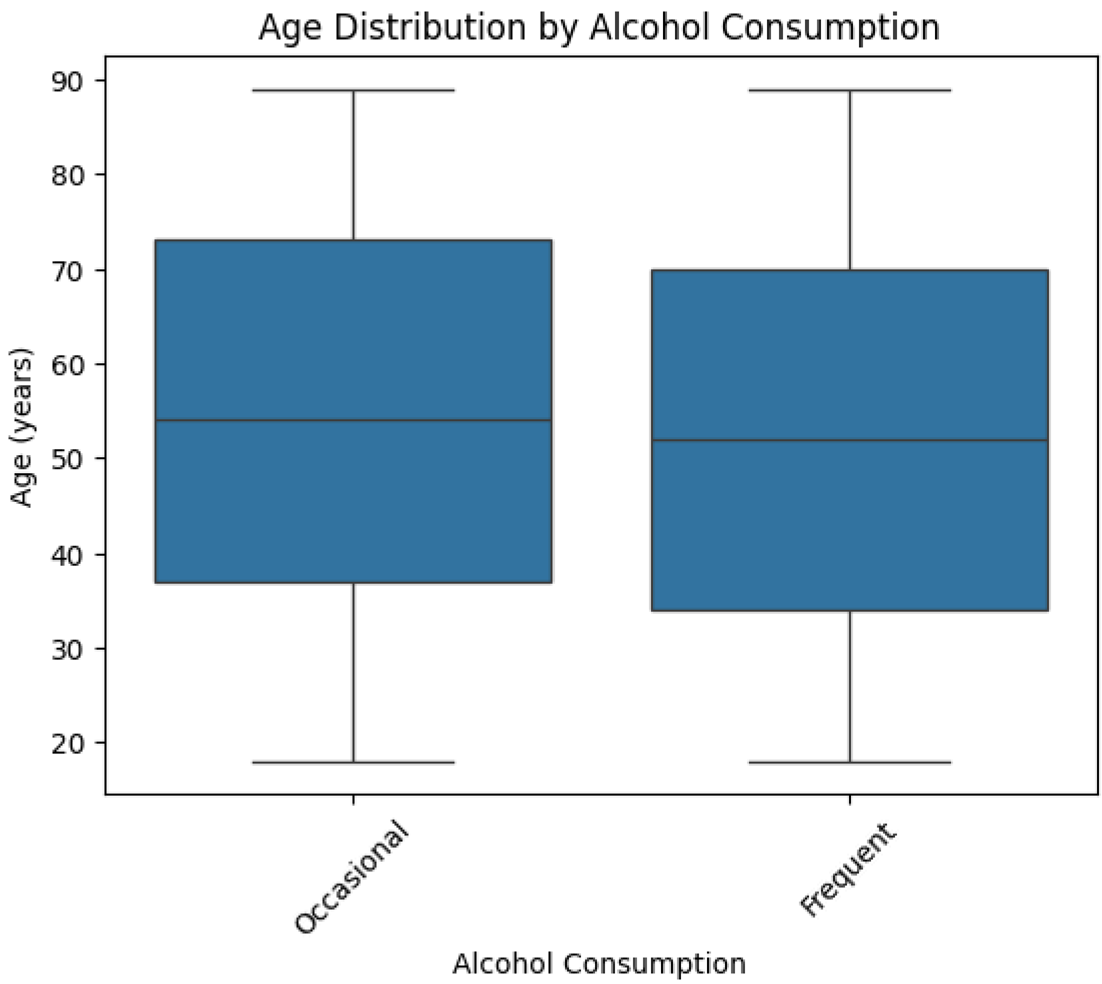
```python
#Assigning all categorical variables
categorical_features = ('Gender', 'Physical Activity Level', 'Smoking Status',
       'Alcohol Consumption', 'Diet', 'Chronic Diseases', 'Medication Use',
       'Family History', 'Mental Health Status', 'Sleep Patterns',
       'Education Level', 'Income Level')


for col in categorical_features:
    sns.boxplot(x=col, y='Age (years)', data=df)
    plt.xticks(rotation=45)
    plt.title(f'Age Distribution by {col}')
    plt.show()
```

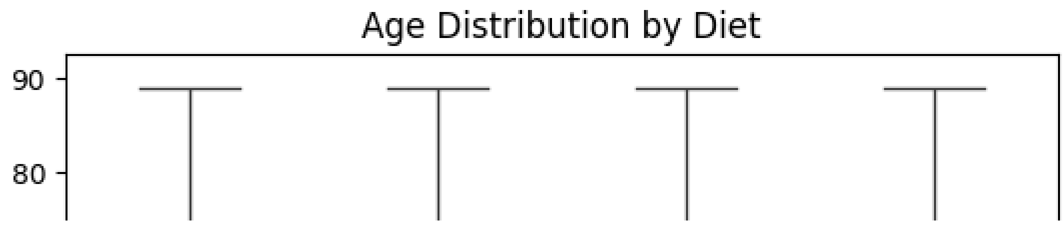

Age Distribution by Gender
90
80
70
60
50
40
30
20
Age (years)
Male
Female
Gender

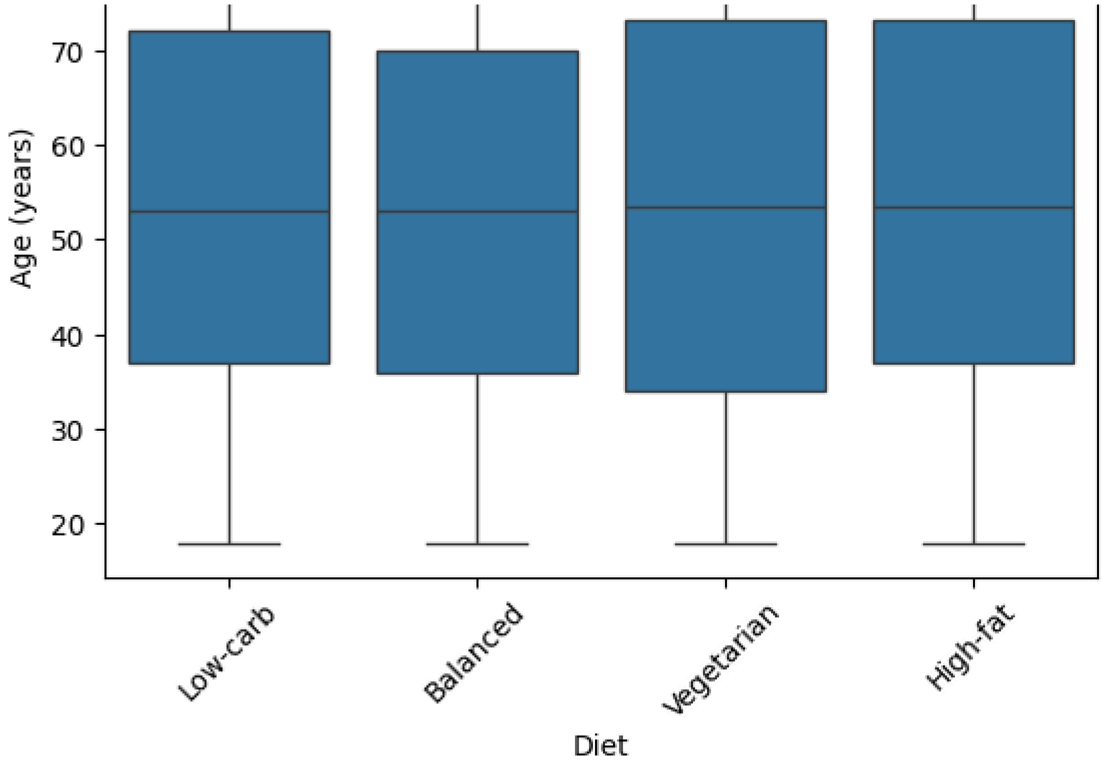

Age Distribution by Physical Activity Level
90
80
70
60
50
40
30
20
Age (years)
Moderate
Low
High
Physical Activity Level

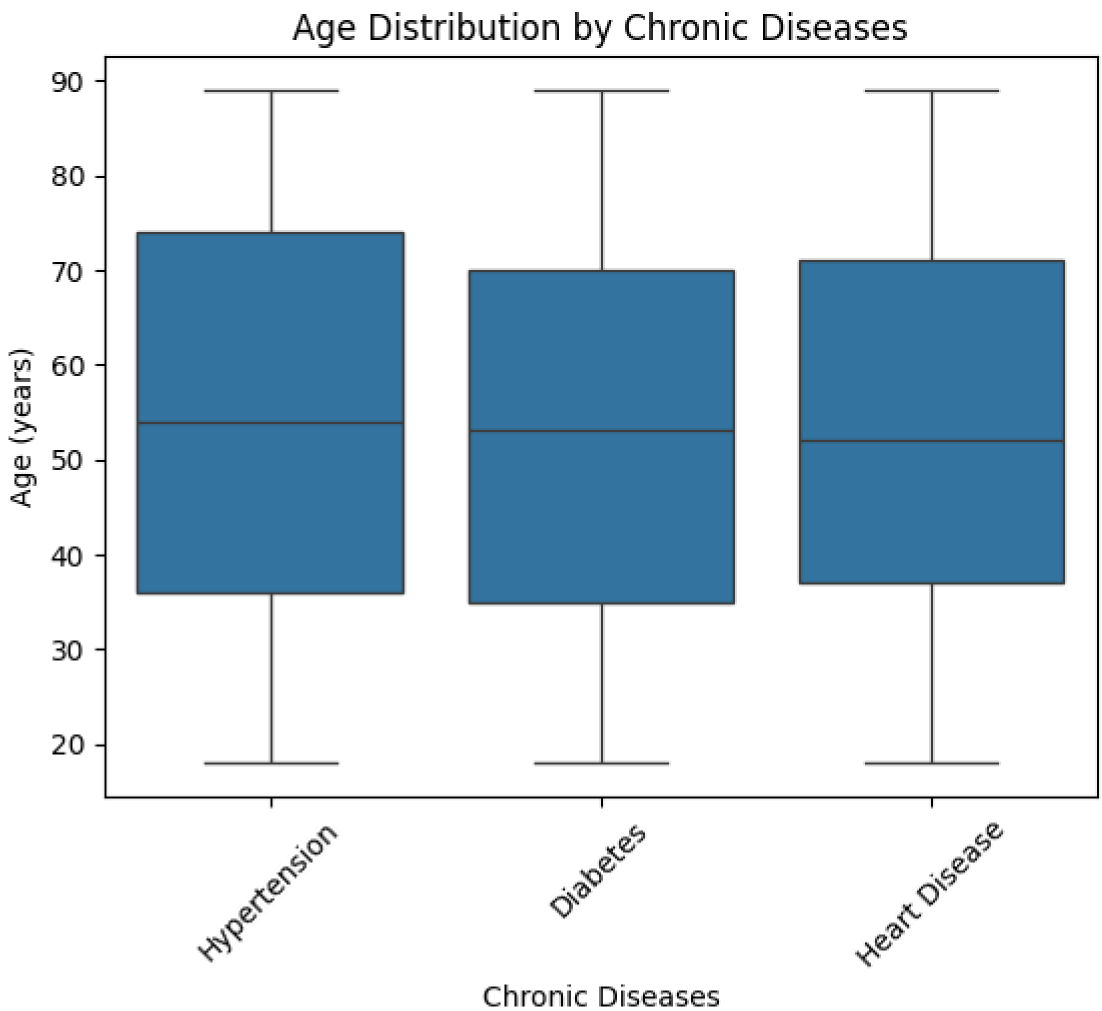

Age Distribution by Smoking Status
90

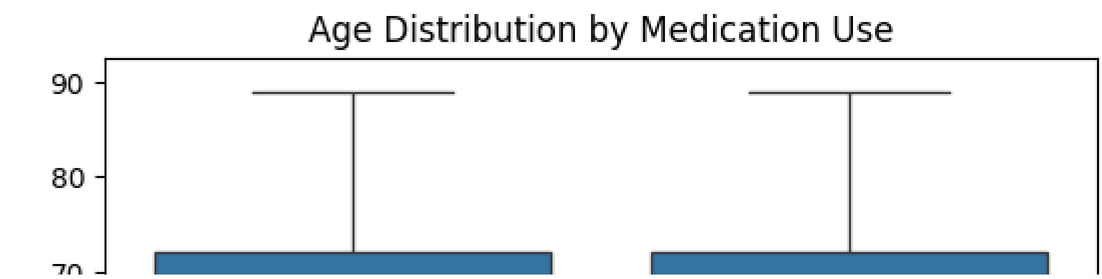

80
70
60
50
40
30
20
Age (years)
Former
Current
Never
Smoking Status

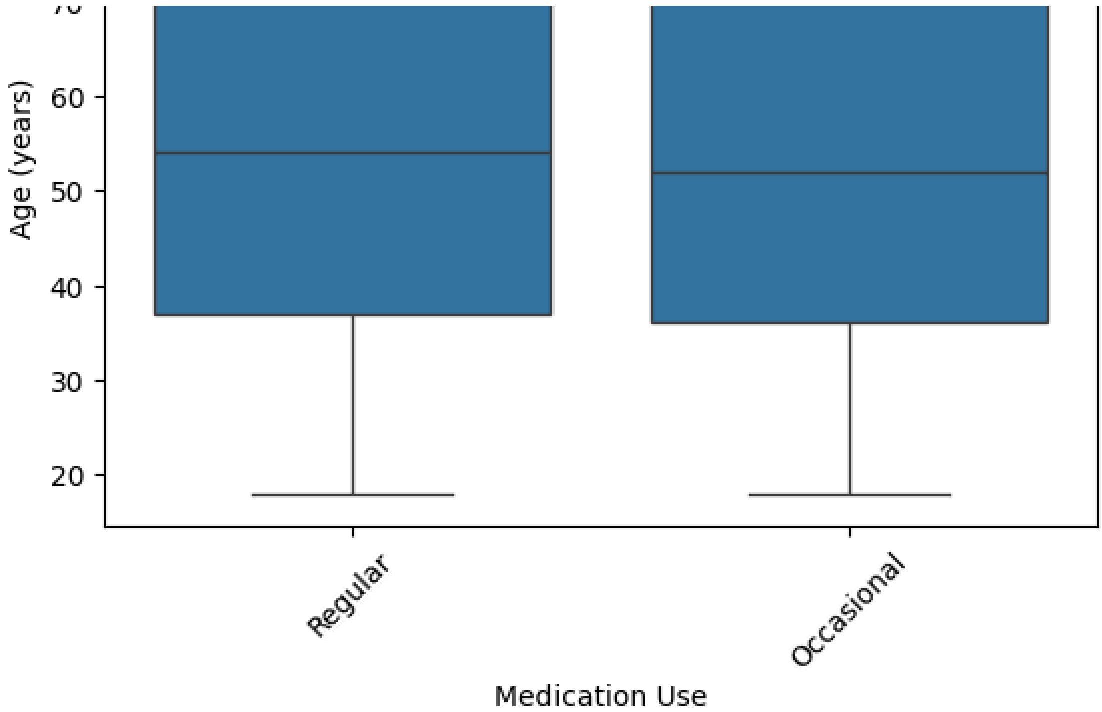

Age Distribution by Alcohol Consumption
90
80
70
60
50
40
30
20
Age (years)
Occasional
Frequent
Alcohol Consumption

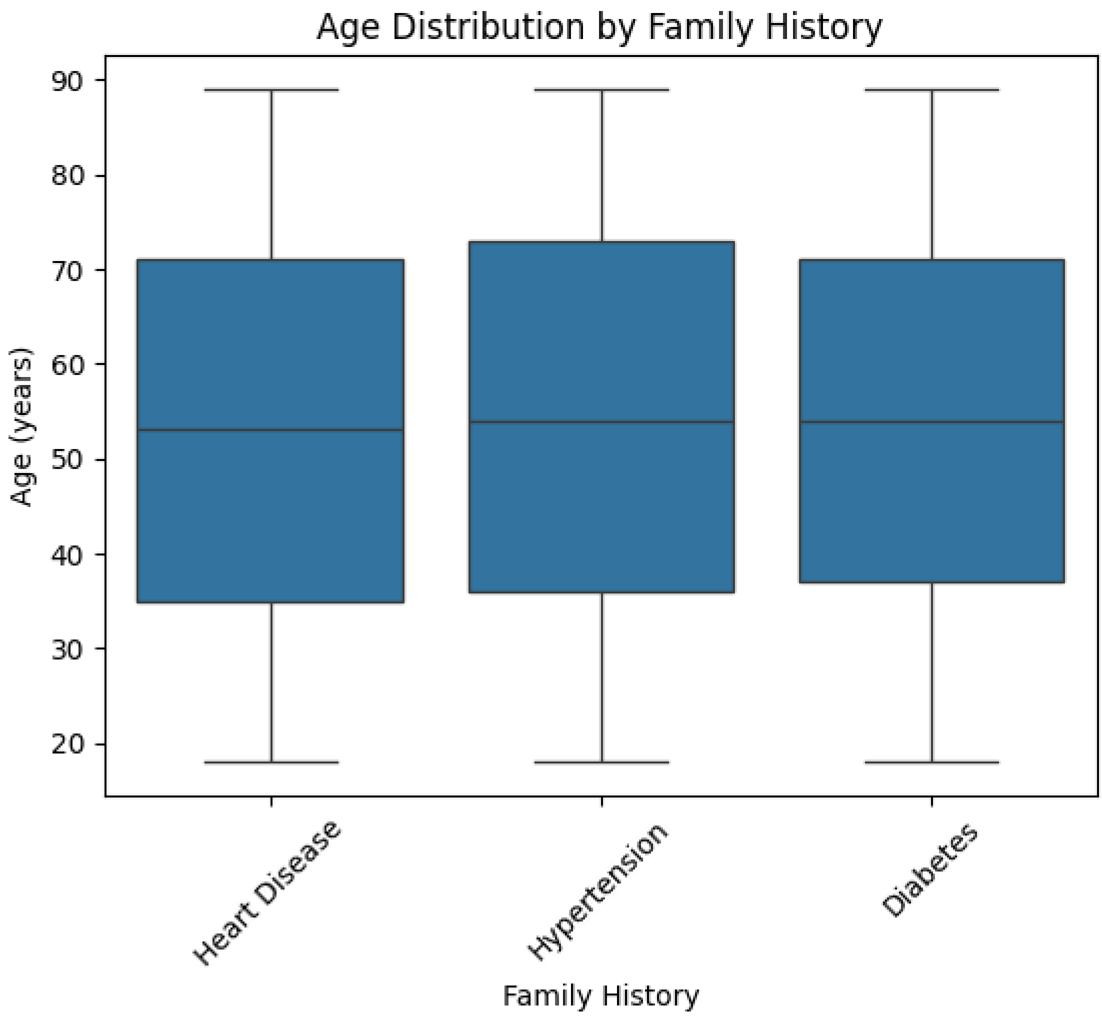

Age Distribution by Diet
90
80

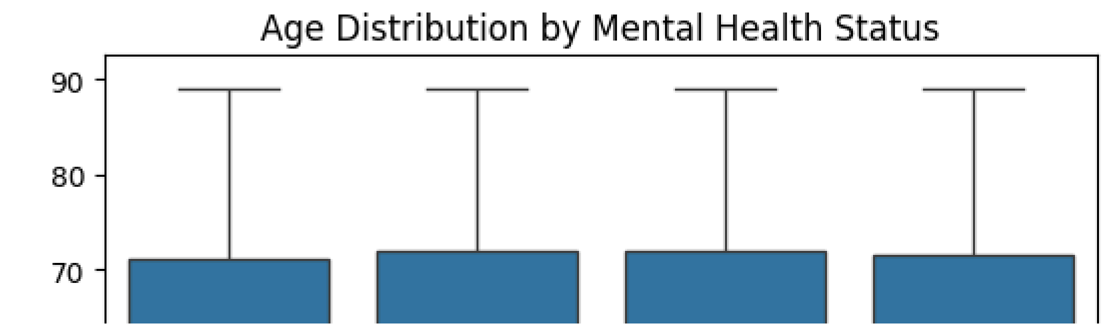

Age (years)
70
60
50
40
30
20
Low-carb
Balanced
Vegetarian
High-fat
Diet

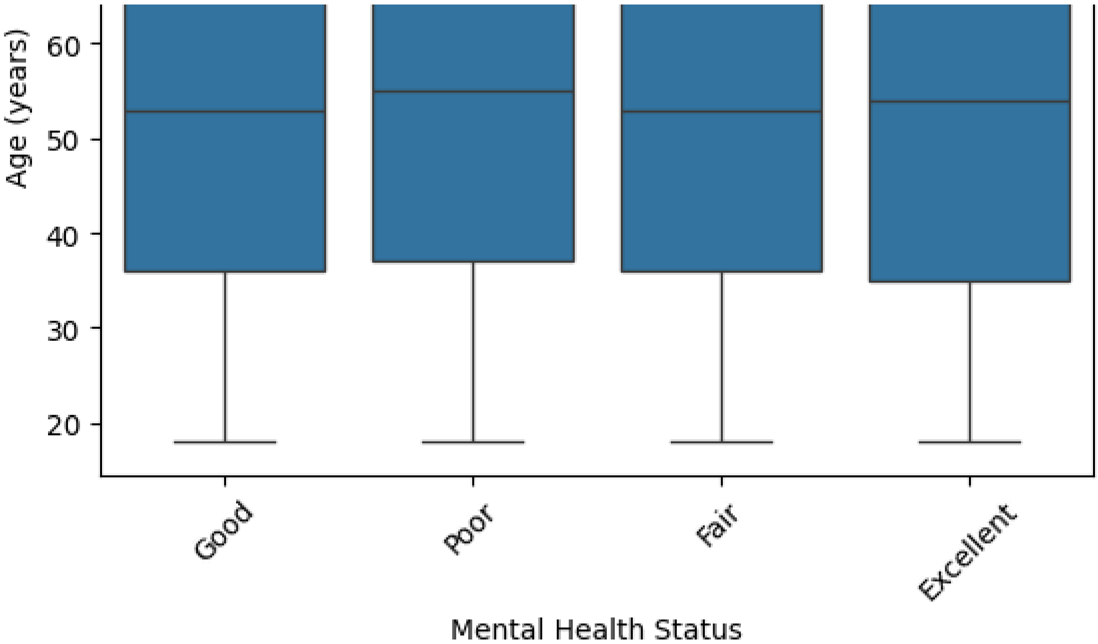

Age Distribution by Chronic Diseases
Age (years)
90
80
70
60
50
40
30
20
Hypertension
Diabetes
Heart Disease
Chronic Diseases

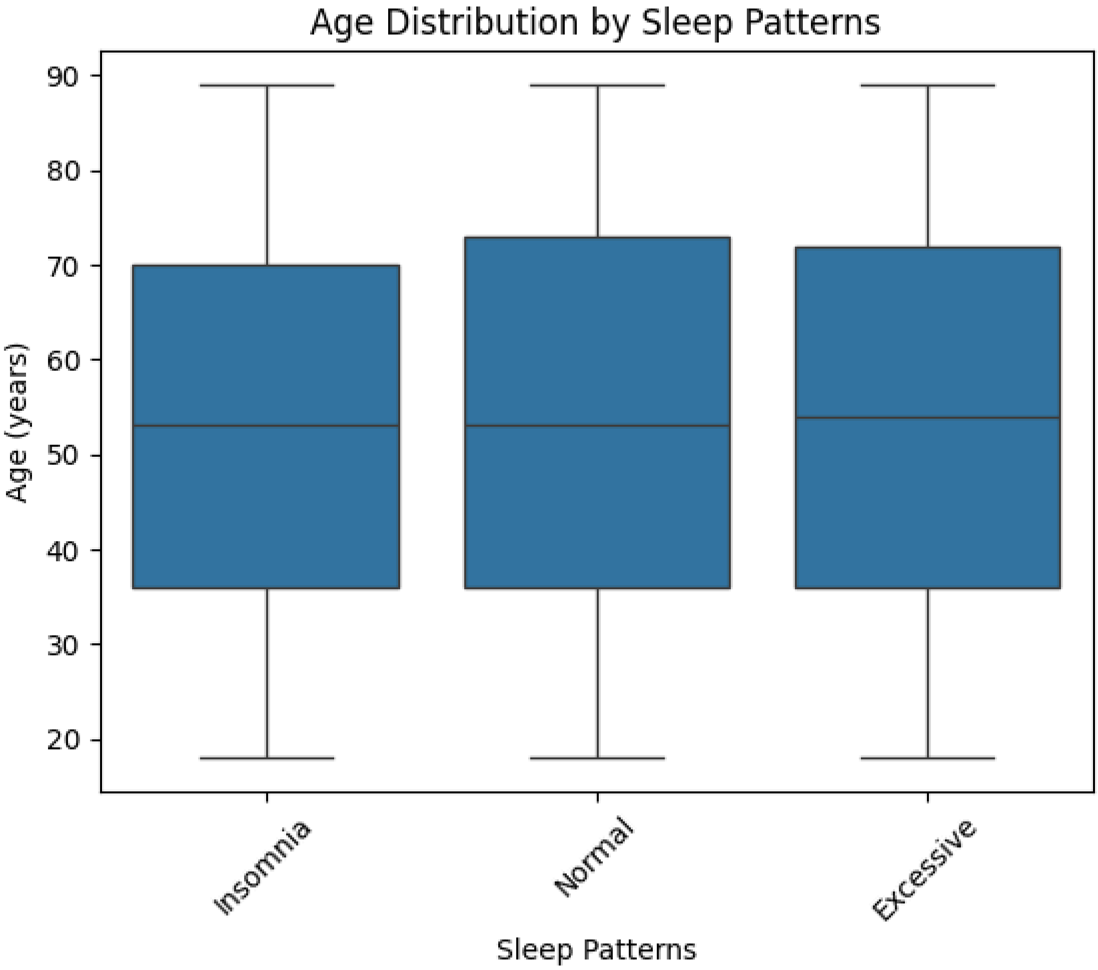

Age Distribution by Medication Use
90
80

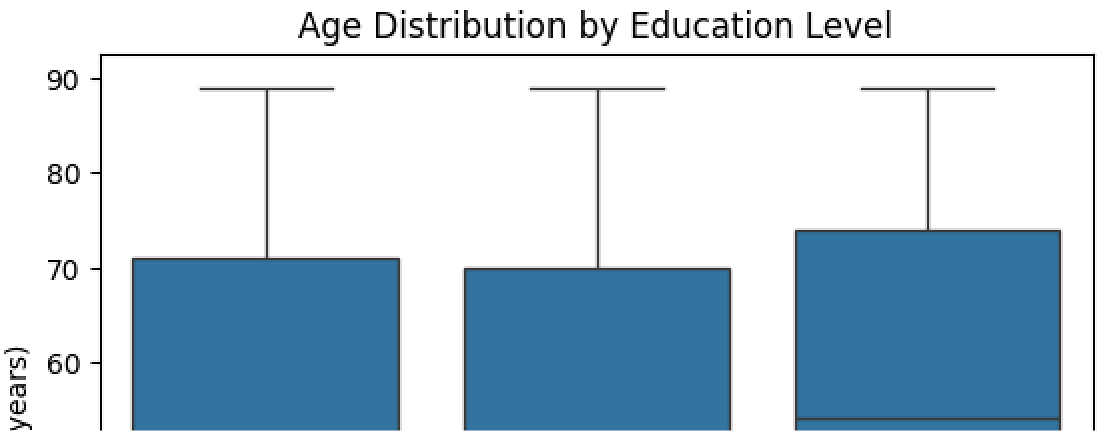

Age (years)
70
60
50
40
30
20
Regular
Occasional
Medication Use

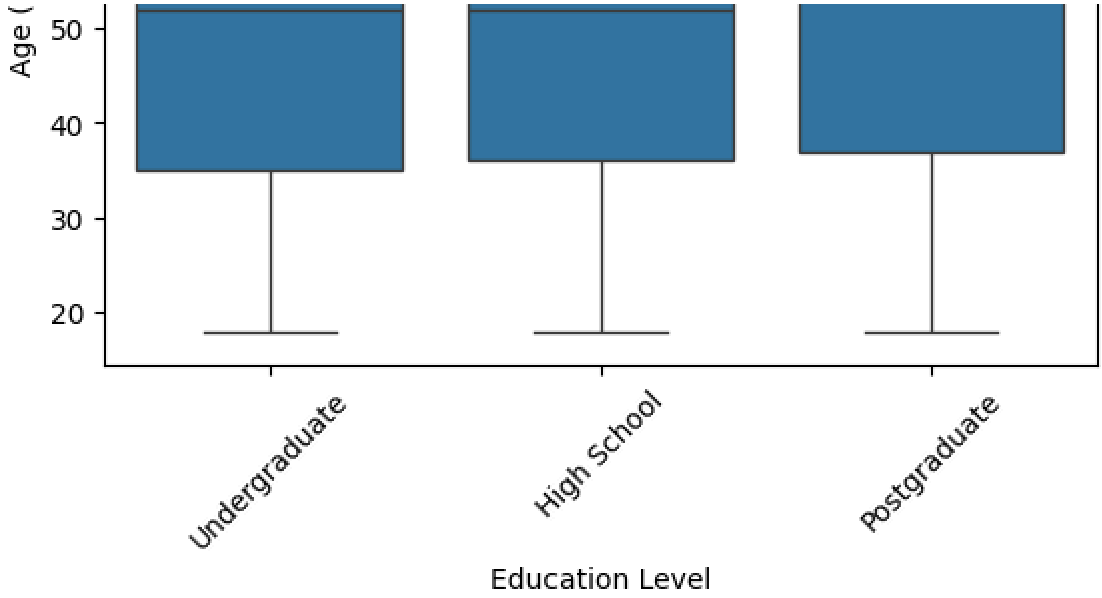

Age Distribution by Family History
Age (years)
90
80
70
60
50
40
30
20
Heart Disease
Hypertension
Diabetes
Family History

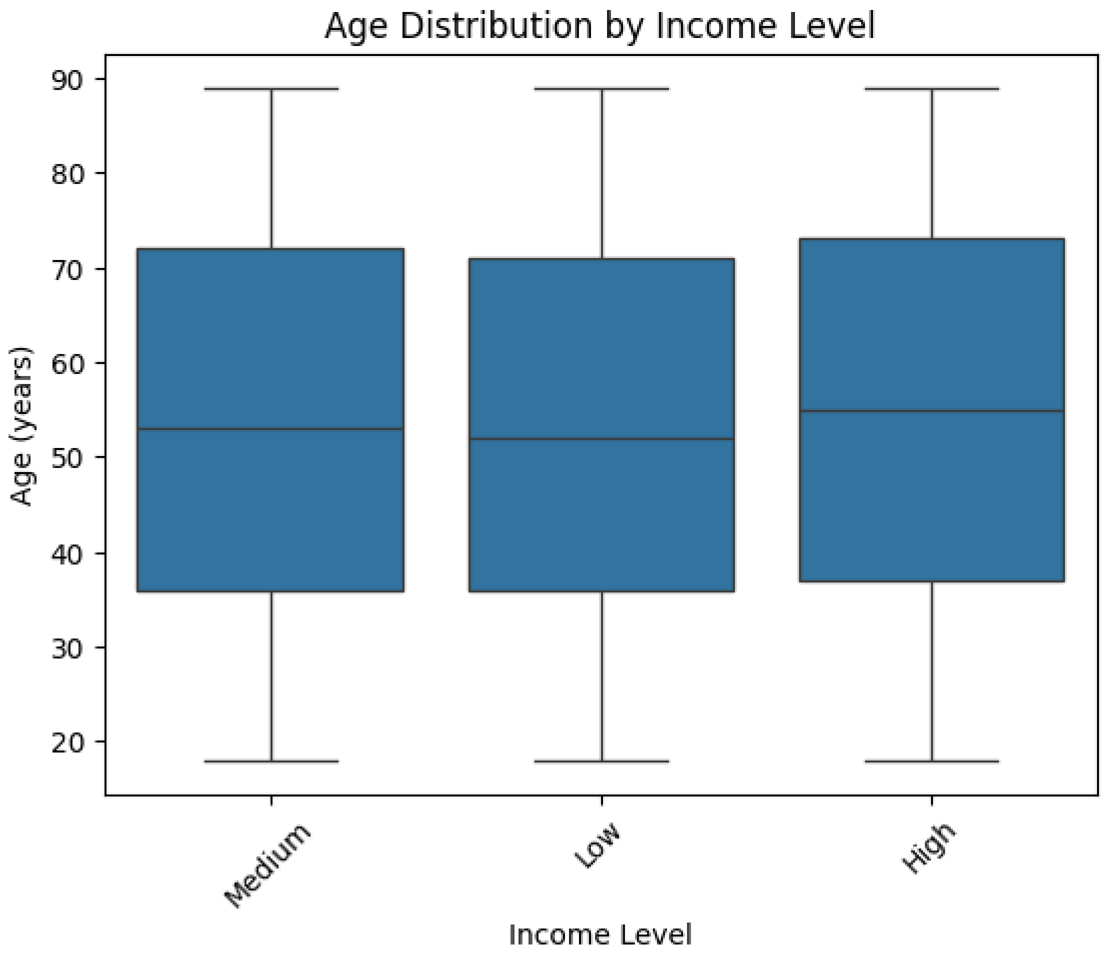

Age Distribution by Mental Health Status
90
80
70


Age (years)
60
50
40
30
20
Good
Poor
Fair
Excellent
Mental Health Status

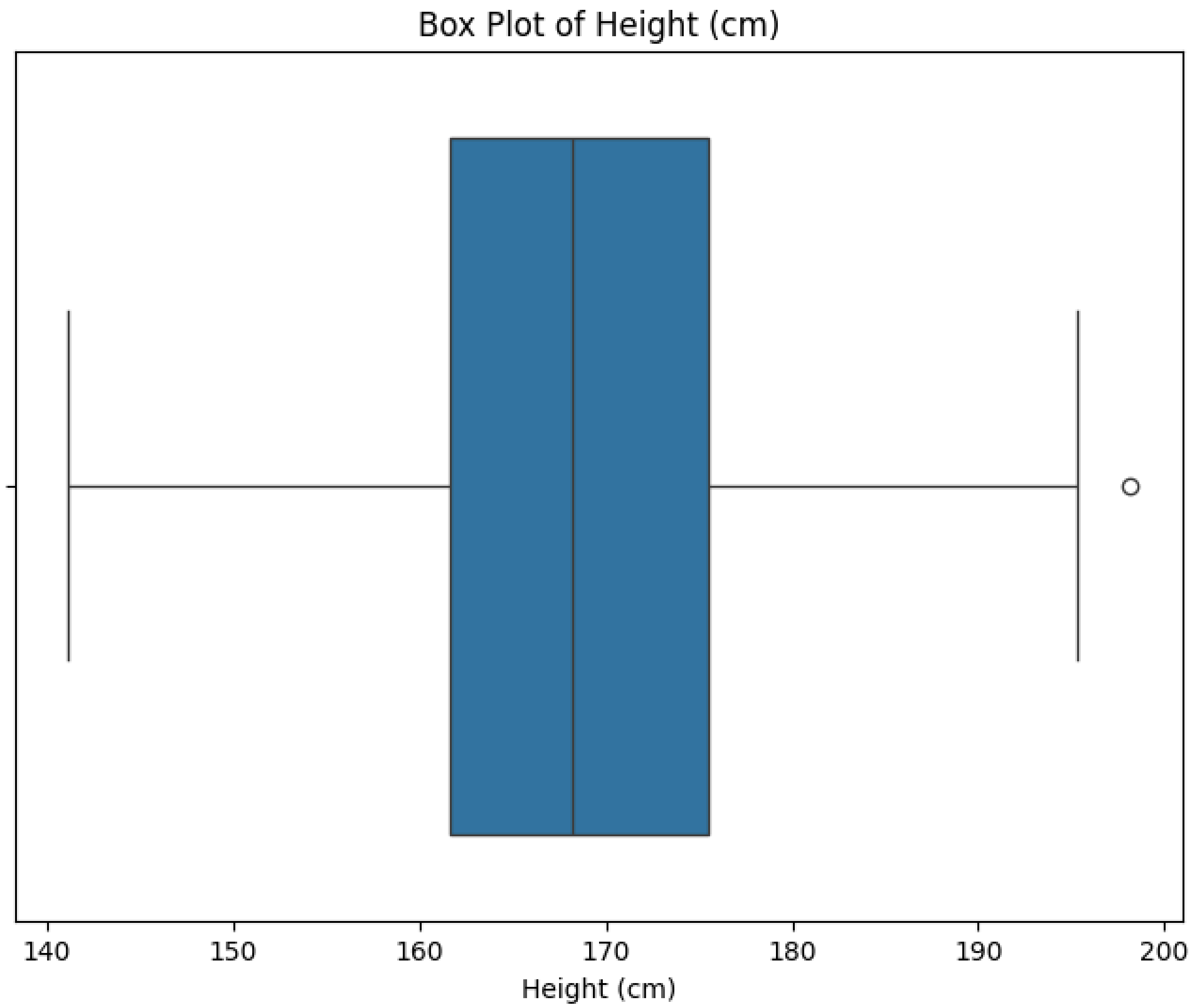

Age Distribution by Sleep Patterns
90
80
70
60
50
40
30
20
Age (years)
Insomnia
Normal
Excessive
Sleep Patterns

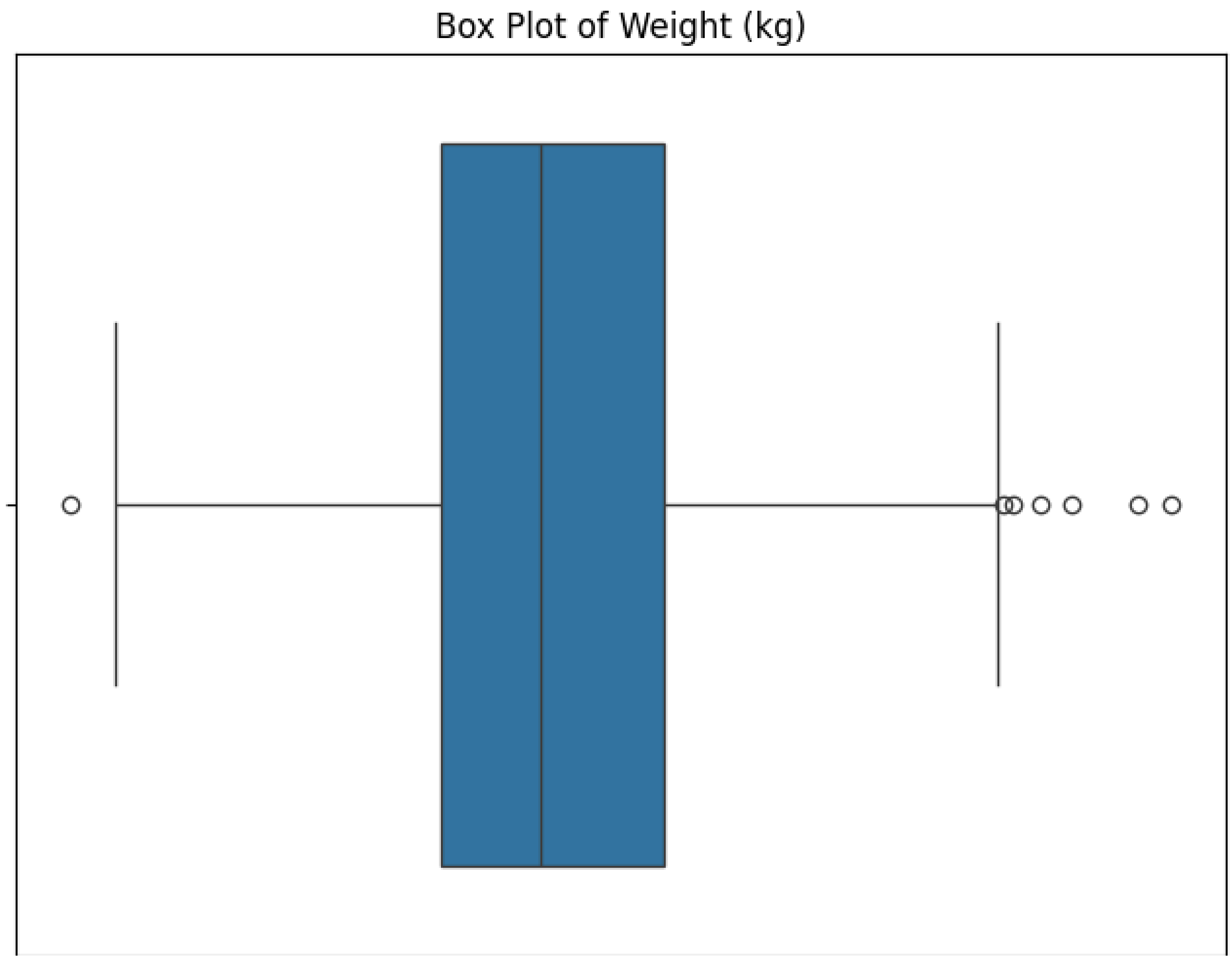

Age Distribution by Education Level
90
80
70
60
years)


Age (
50
40
30
20
Undergraduate
High School
Postgraduate
Education Level

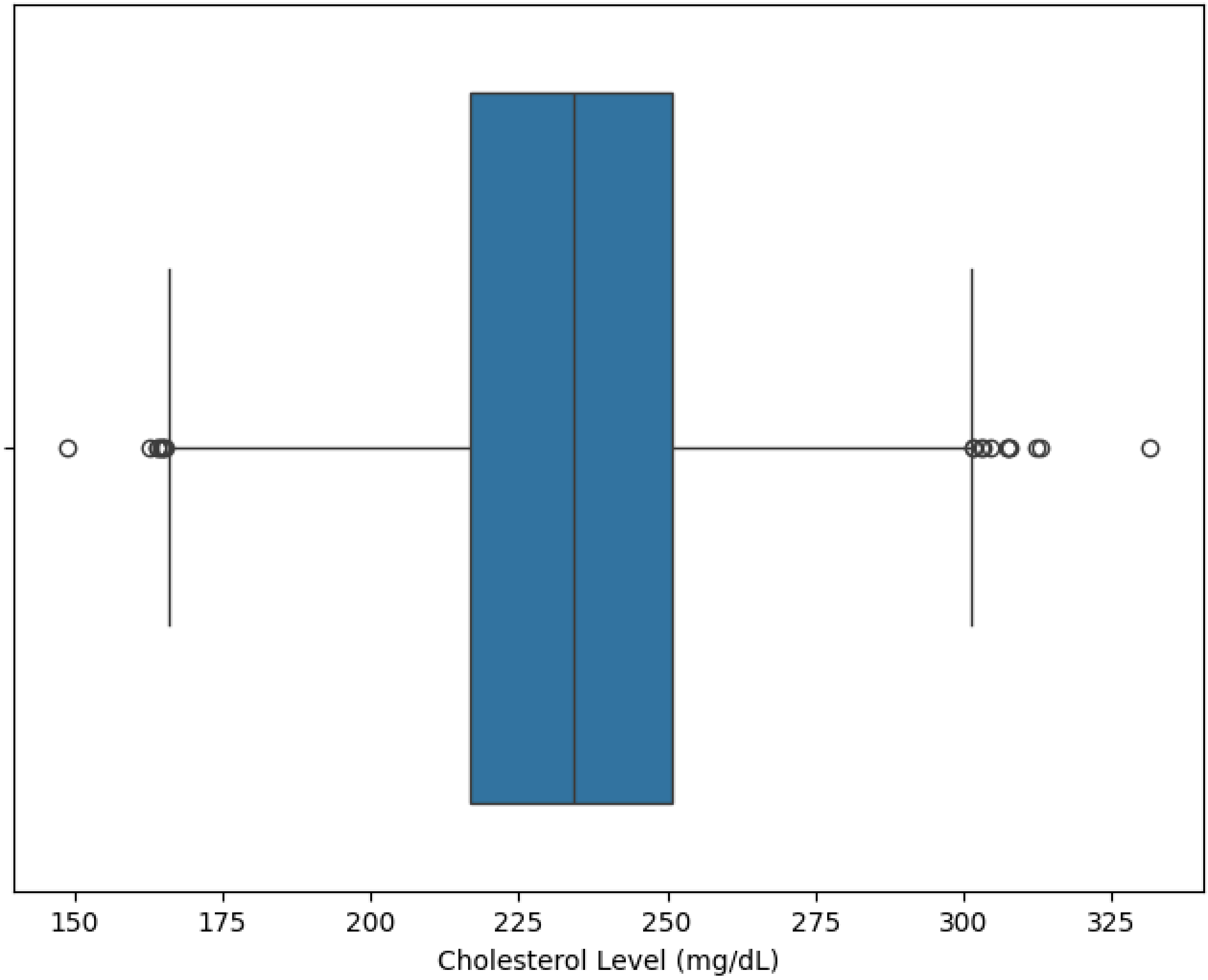

Age Distribution by Income Level
90
80
70
60
50
40
30
20
Age (years)
Medium
Low
High
Income Level

```
# prompt: Generate box plots for all numerical features

for col in numerical_features:
    plt.figure(figsize=(8, 6))  # Adjust figure size as needed
    sns.boxplot(x=df[col])
    plt.title(f'Box Plot of {col}')
    plt.show()
```

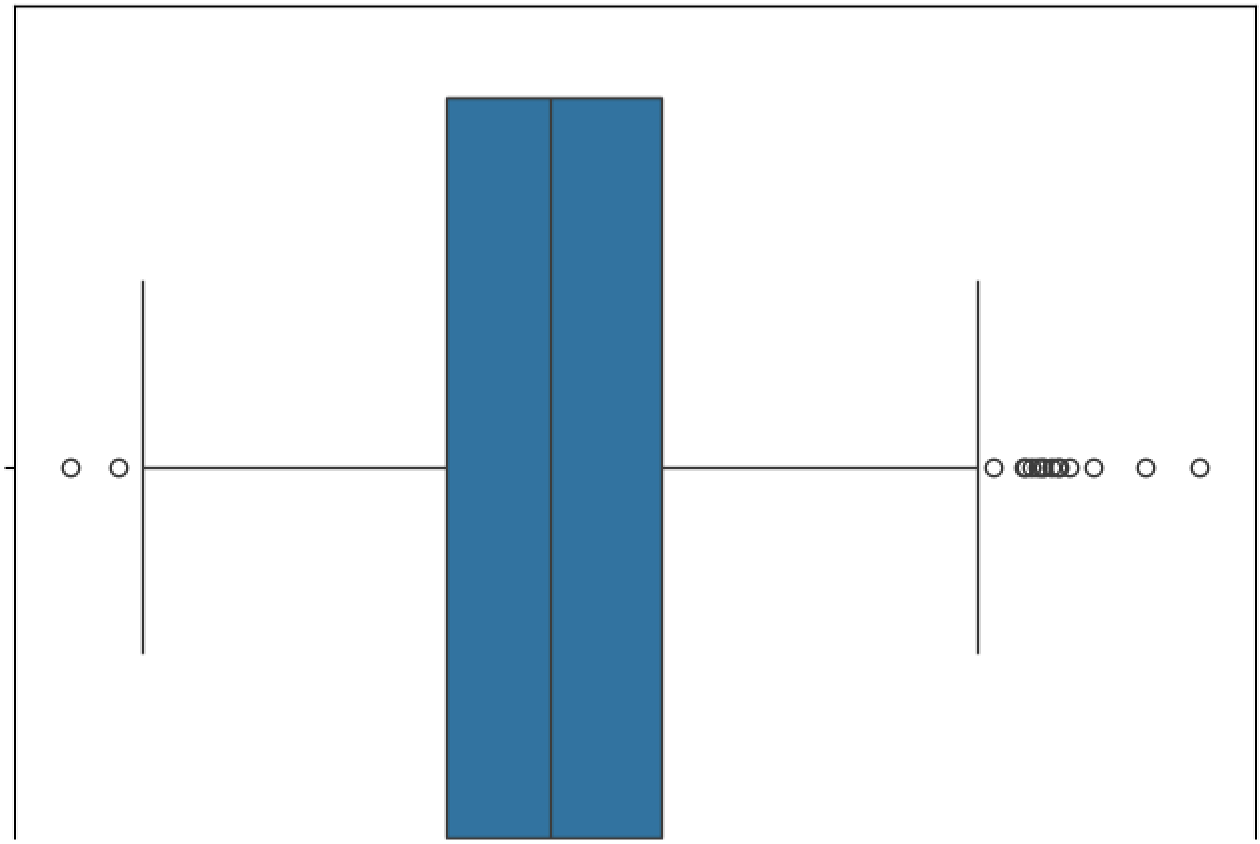

Box Plot of Height (cm)
140
150
160
170
180
190
200
Height (cm)

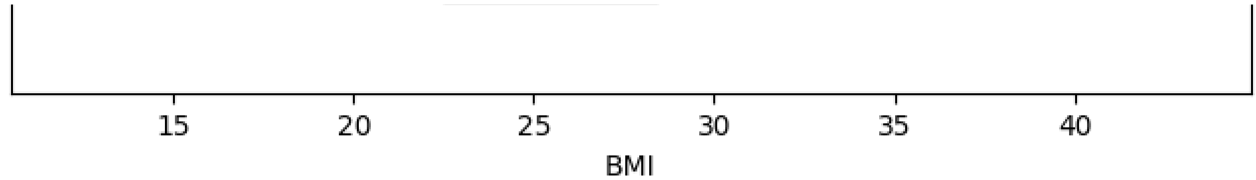

Box Plot of Weight (kg)

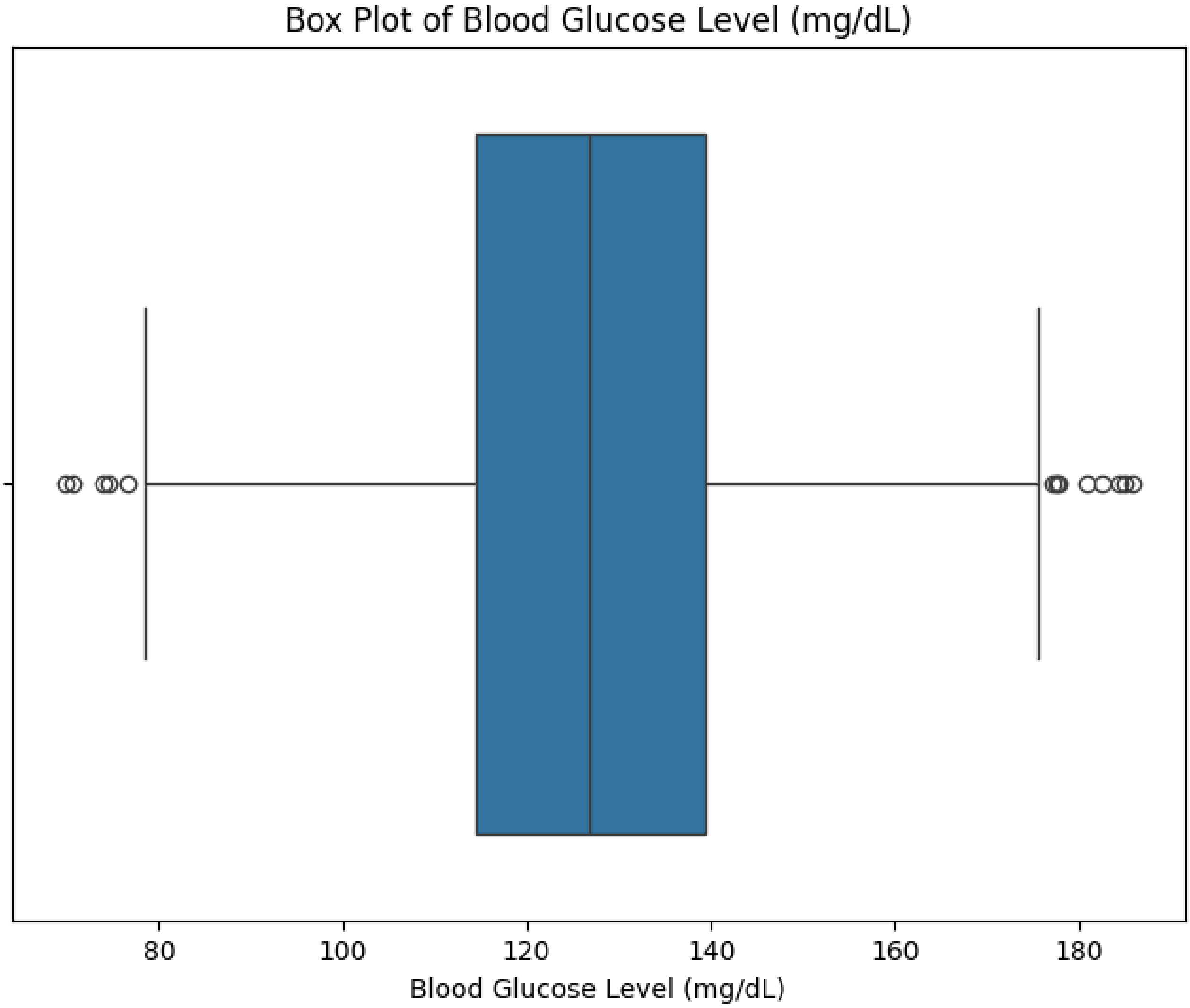
Box Plot of Cholesterol Level (mg/dL)

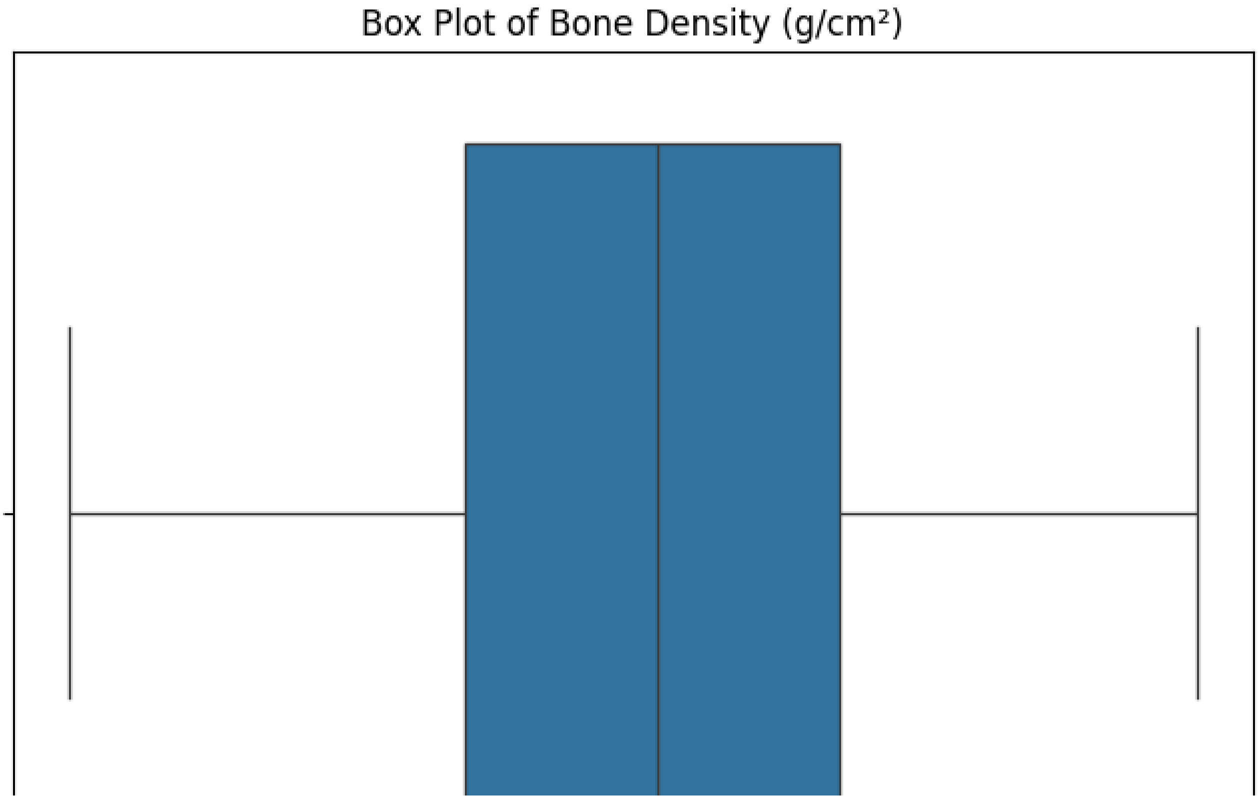


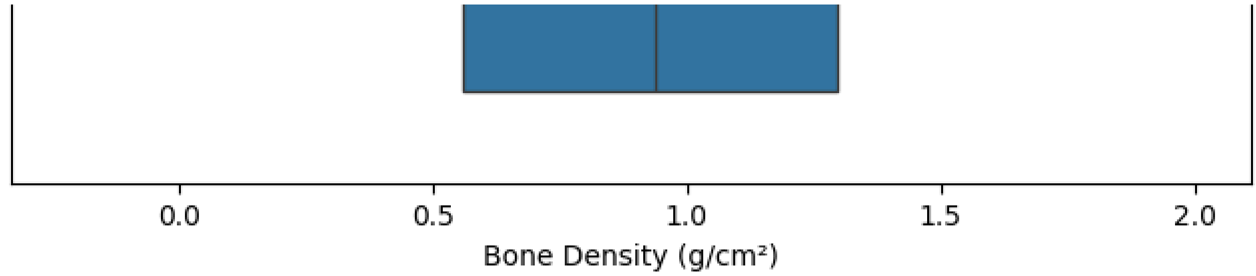
Box Plot of BMI

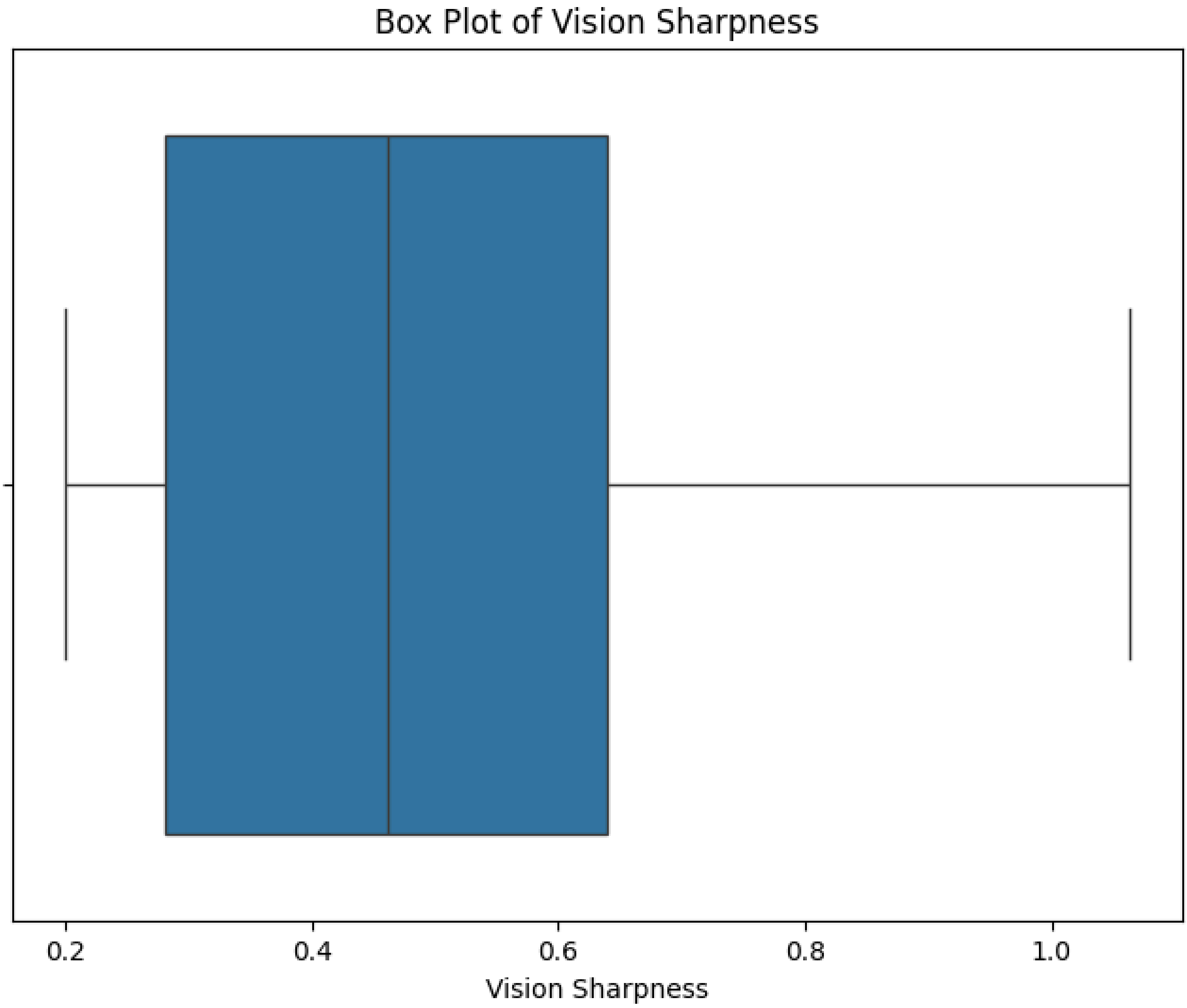


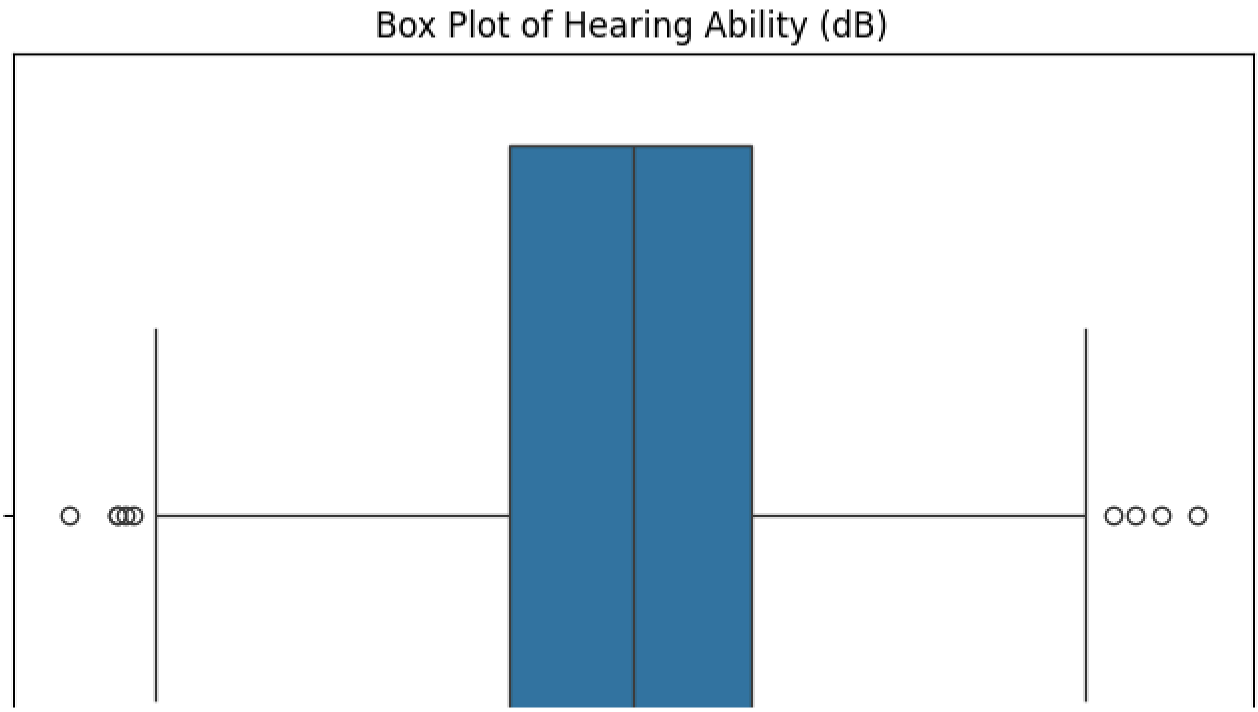

15
20
25
30
35
40
BMI

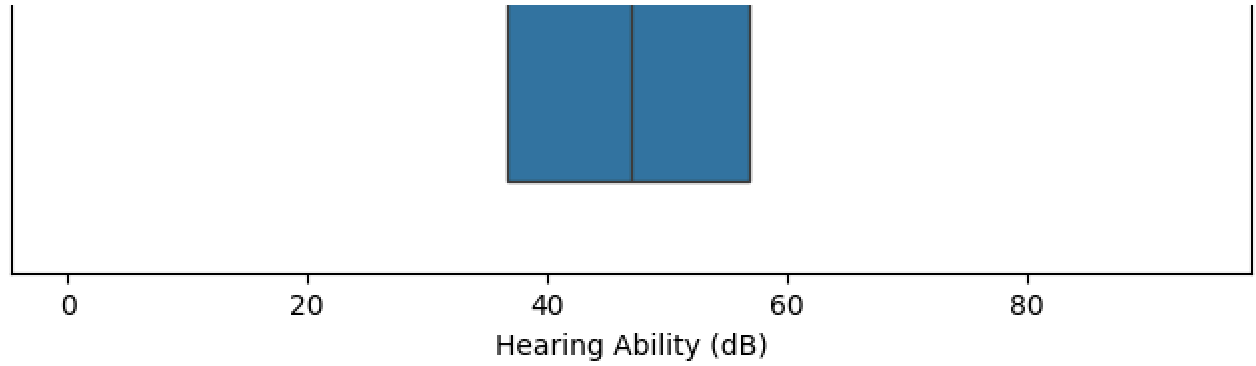

Box Plot of Blood Glucose Level (mg/dL)
80
100
120
140
160
180
Blood Glucose Level (mg/dL)

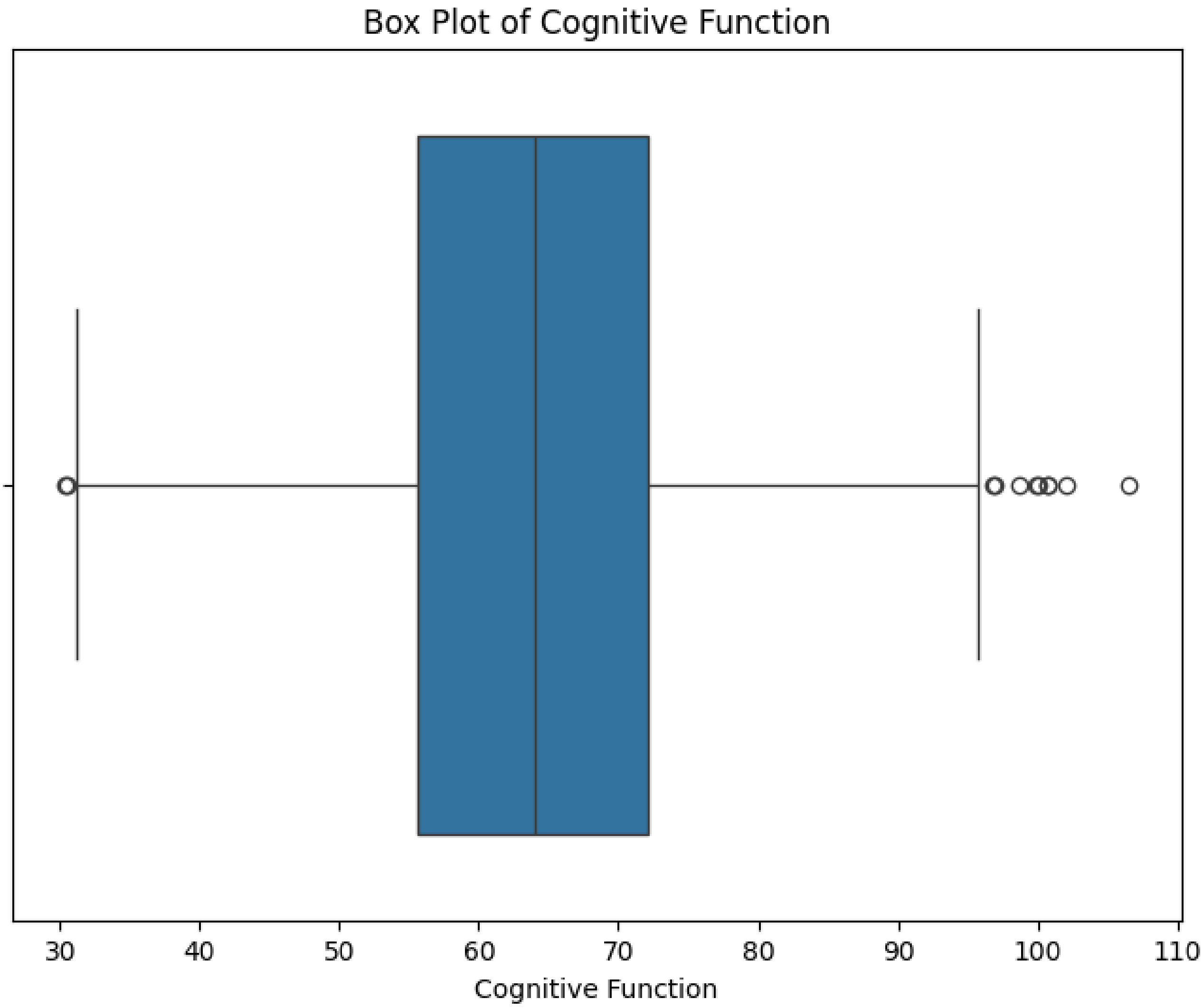

Box Plot of Bone Density (g/cm²)

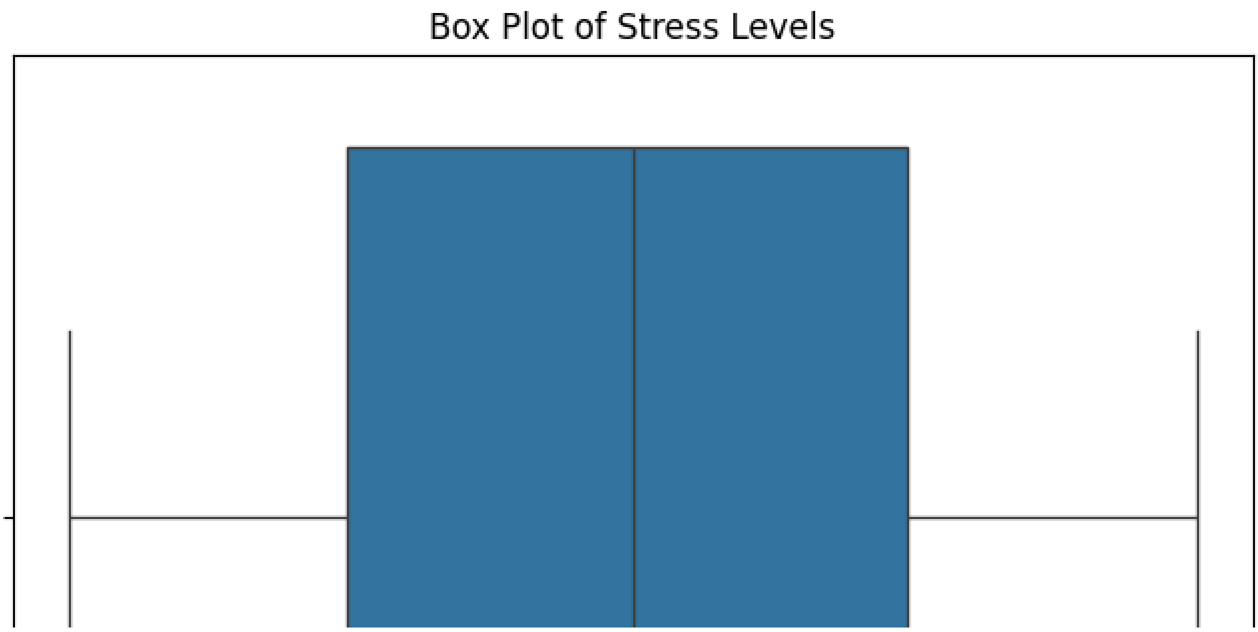

0.0
0.5
1.0
1.5
2.0
Bone Density (g/cm²)

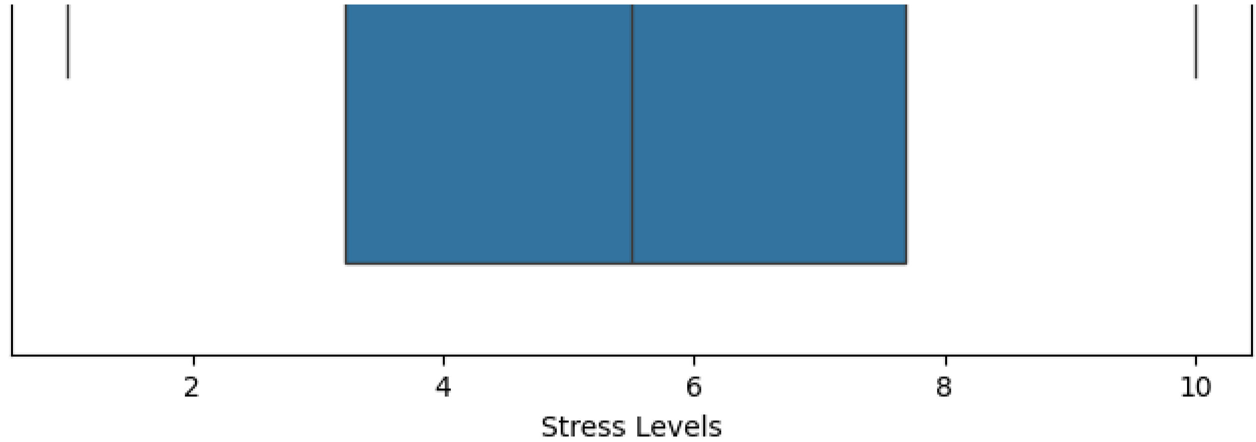

Box Plot of Vision Sharpness
0.2
0.4
0.6
0.8
1.0
Vision Sharpness

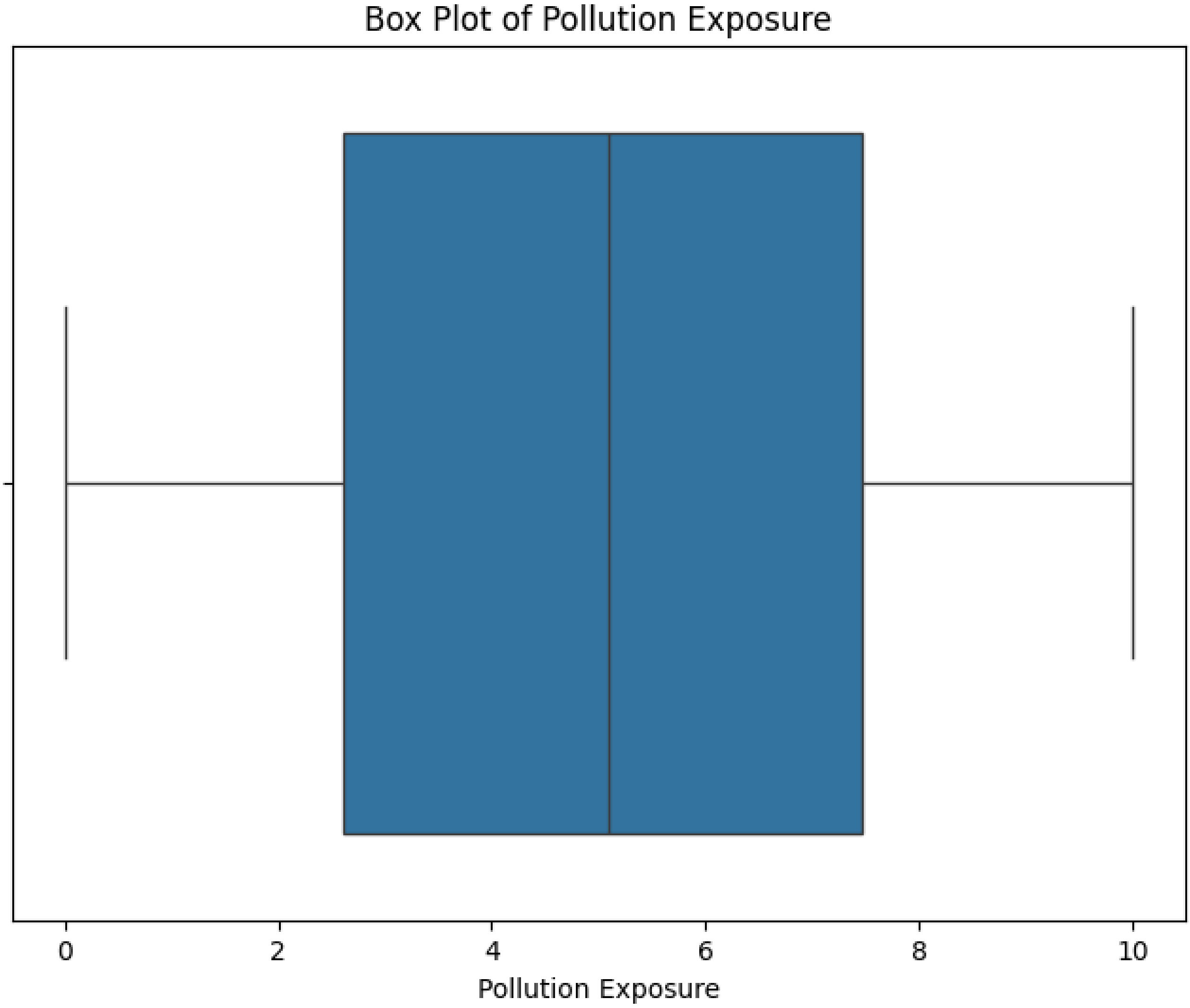

Box Plot of Hearing Ability (dB)

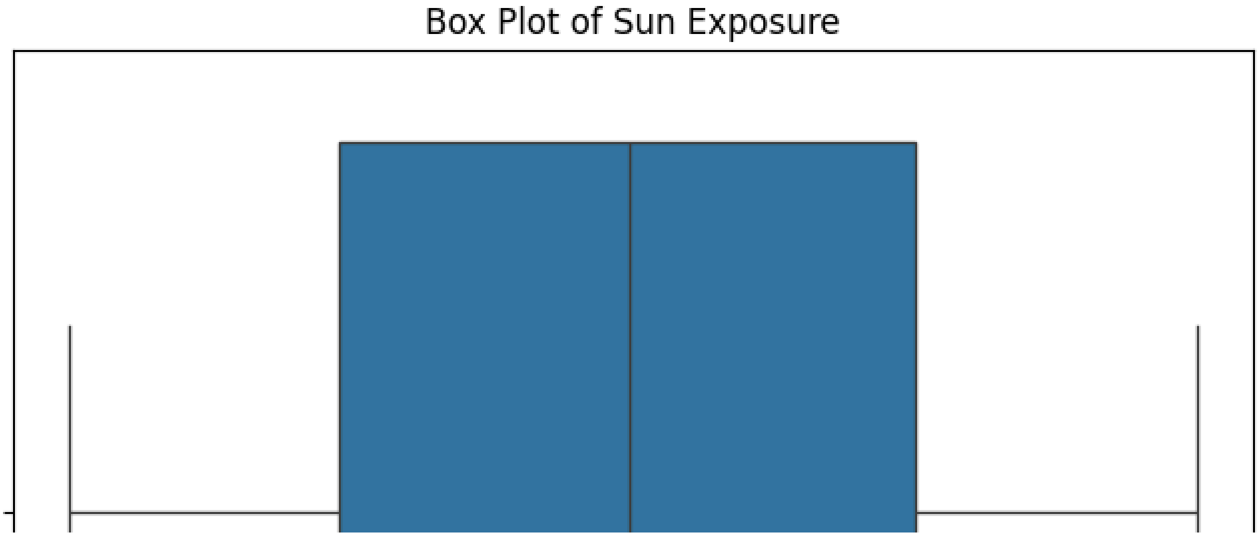

0
20
40
60
80
Hearing Ability (dB)

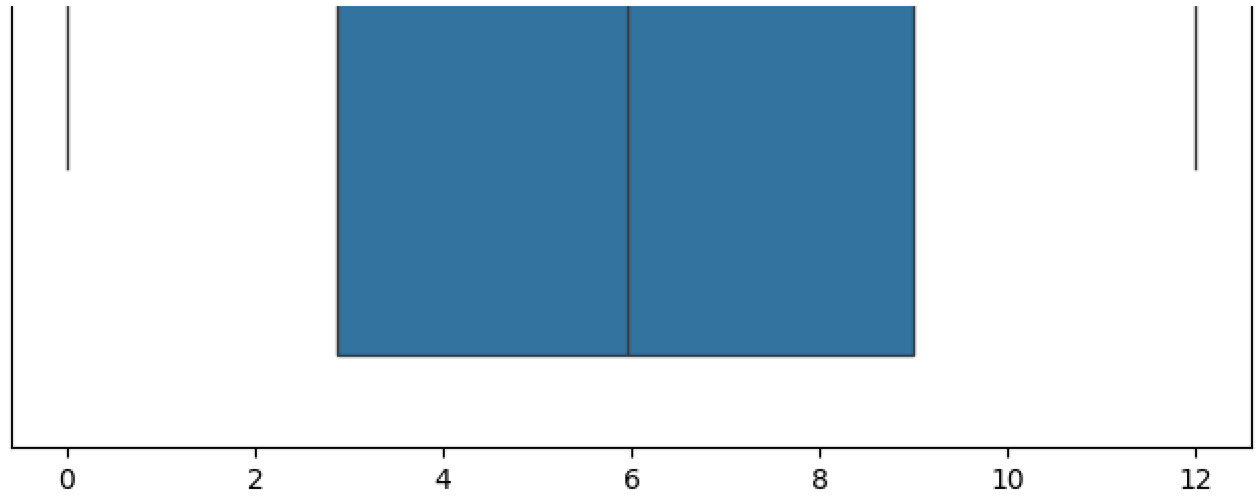

Box Plot of Cognitive Function
30
40
50
60
70
80
90
100
110
Cognitive Function

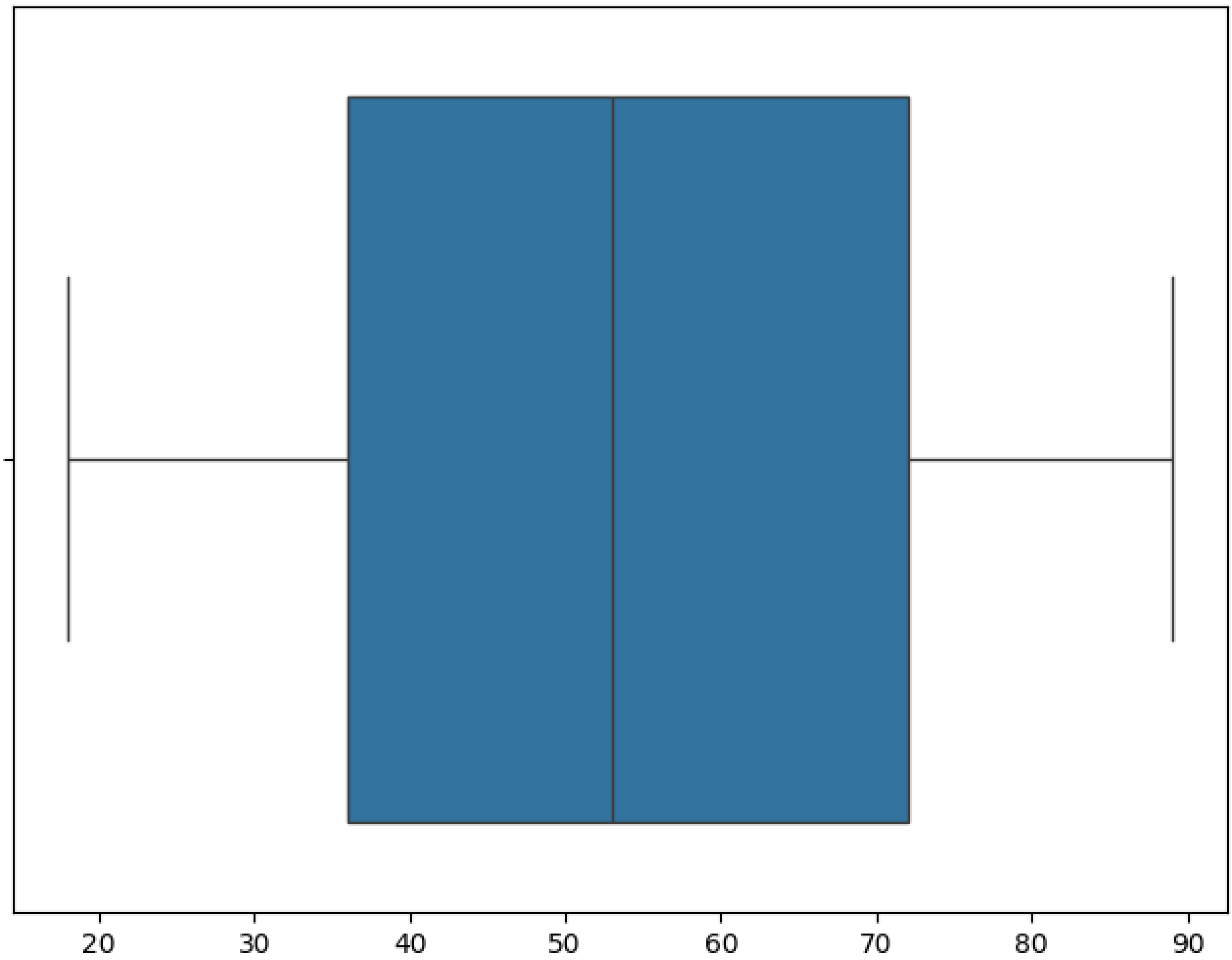

Box Plot of Stress Levels

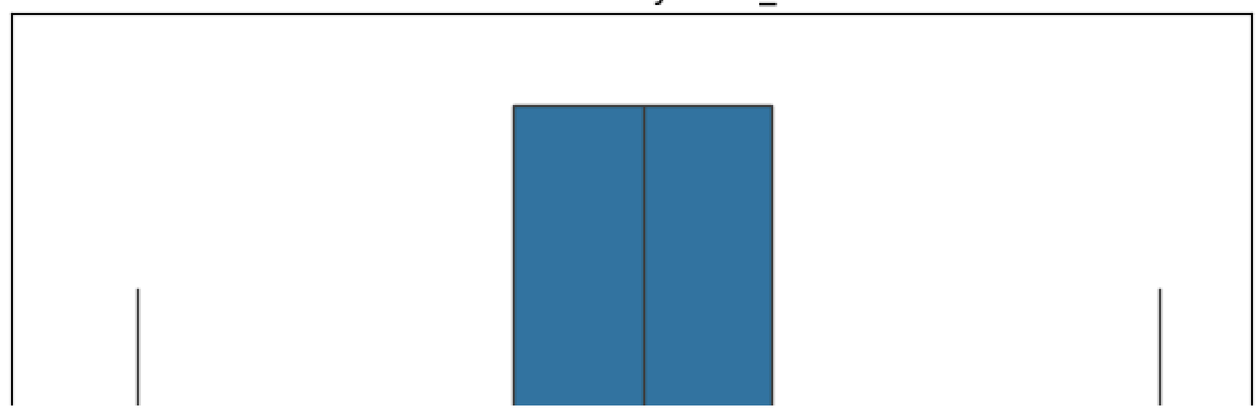

2
4
6
8
10
Stress Levels

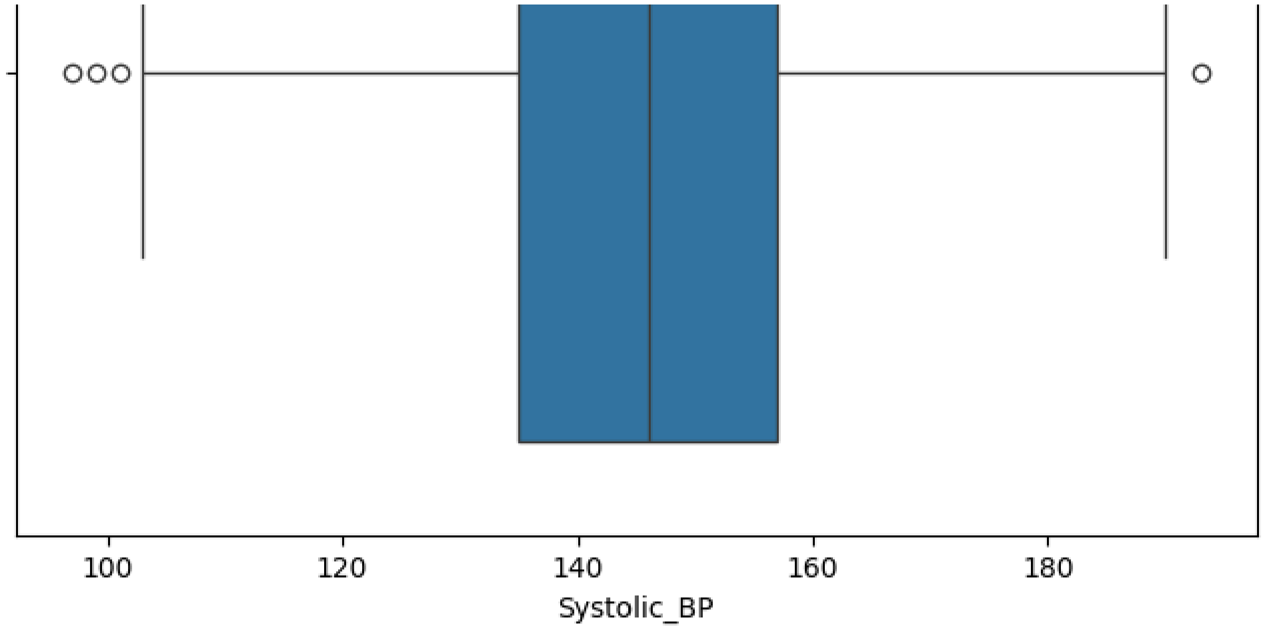

Box Plot of Pollution Exposure
0
2
4
6
8
10
Pollution Exposure


Box Plot of Sun Exposure

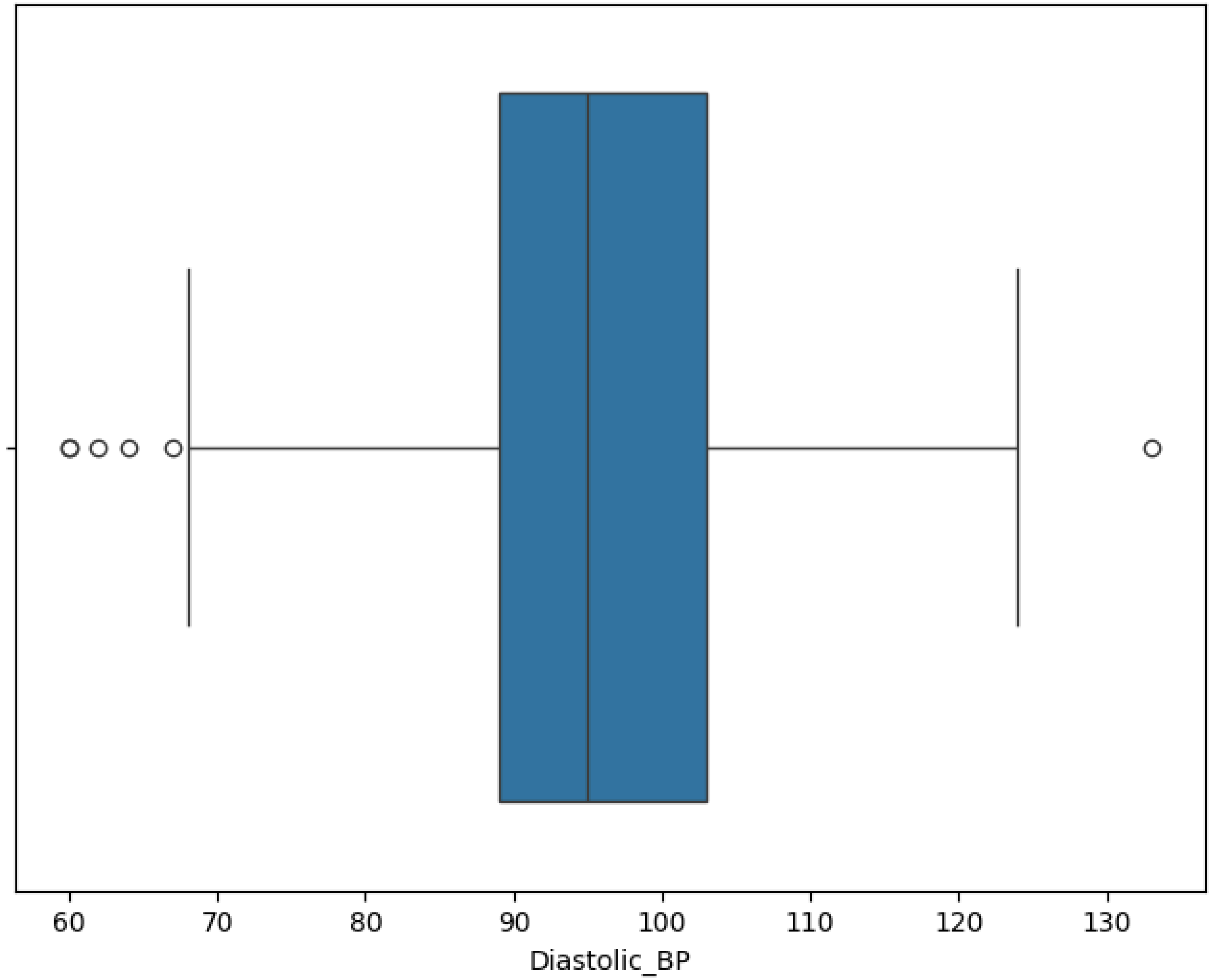

0
2
4
6
8
10
12
Sun Exposure


Box Plot of Age (years)
20
30
40
50
60
70
80
90
Age (years)


Box Plot of Systolic_BP



Box Plot of Diastolic_BP



```
nan_columns = df.columns[df.isnull().any()]
print("Columns with NaN values:", nan_columns)
```

```
Columns with NaN values: Index(['Alcohol Consumption', 'Chronic Diseases', 'M
       'Family History', 'Education Level'],
      dtype='object')
```

```
for col in categorical_features:
    df[col] = df[col].fillna("Don't Have")
```

```
for col in categorical_features:
    print(f"Unique values for '{col}': {df[col].unique()}")
```

```
Unique values for 'Gender': ['Male' 'Female']
Unique values for 'Physical Activity Level': ['Moderate' 'Low' 'High']
Unique values for 'Smoking Status': ['Former' 'Current' 'Never']
Unique values for 'Alcohol Consumption': ["Don't Have" 'Occasional' 'Frequent
Unique values for 'Diet': ['Low-carb' 'Balanced' 'Vegetarian' 'High-fat']
Unique values for 'Chronic Diseases': ["Don't Have" 'Hypertension' 'Diabetes'
Unique values for 'Medication Use': ["Don't Have" 'Regular' 'Occasional']
Unique values for 'Family History': ["Don't Have" 'Heart Disease' 'Hypertensi
Unique values for 'Mental Health Status': ['Good' 'Poor' 'Fair' 'Excellent']
Unique values for 'Sleep Patterns': ['Insomnia' 'Normal' 'Excessive']
Unique values for 'Education Level': ["Don't Have" 'Undergraduate' 'High Scho
Unique values for 'Income Level': ['Medium' 'Low' 'High']
```

```
print(df.isnull().sum())
```

```
Gender                         0
Height (cm)                    0
Weight (kg)                    0
Blood Pressure (s/d)           0
Cholesterol Level (mg/dL)      0
BMI                            0
Blood Glucose Level (mg/dL)    0
Bone Density (g/cm²)           0
Vision Sharpness               0
Hearing Ability (dB)           0
Physical Activity Level        0
Smoking Status                 0
Alcohol Consumption            0
Diet                           0
Chronic Diseases               0
Medication Use                 0
Family History                 0
Cognitive Function             0
Mental Health Status           0
Sleep Patterns                 0
Stress Levels                  0
Pollution Exposure             0
Sun Exposure                   0
Education Level                0
Income Level                   0
Age (years)                    0
Systolic_BP                    0
Diastolic_BP                   0
```

```
dtype: int64
```

One Hot Encoding

```
categorical_features = ['Gender', 'Physical Activity Level', 'Smoking Status',
       'Alcohol Consumption', 'Diet', 'Chronic Diseases', 'Medication Use',
       'Family History', 'Mental Health Status', 'Sleep Patterns',
       'Education Level', 'Income Level']
```

```
encoder = OneHotEncoder(handle_unknown='ignore', sparse_output=False)
encoded_features = encoder.fit_transform(df[categorical_features])
encoded_df = pd.DataFrame(encoded_features, columns=encoder.get_feature_names_out
df_encoded = pd.concat([df.drop(categorical_features, axis=1), encoded_df], axis=
print(df_encoded.head())
```

```
   Height (cm)  Weight (kg) Blood Pressure (s/d)  Cholesterol Level (mg/dL)  \
0   171.148359    86.185197              151/109                 259.465814
1   172.946206    79.641937              134/112                 263.630292
2   155.945488    49.167058              160/101                 207.846206
3   169.078298    56.017921               133/94                 253.283779
4   163.758355    73.966304              170/106                 236.119899

         BMI  Blood Glucose Level (mg/dL)  Bone Density (g/cm²)  \
0  29.423017                   157.652848              0.132868
1  26.626847                   118.507805              0.629534
2  20.217553                   143.587550              0.473487
3  19.595270                   137.448581              1.184315
4  27.582078                   145.328695              0.434562

   Vision Sharpness  Hearing Ability (dB)  Cognitive Function  ...  \
0          0.200000             58.786198           44.059172  ...
1          0.267312             54.635270           45.312298  ...
2          0.248667             54.564632           56.246991  ...
3          0.513818             79.722963           55.196092  ...
4          0.306864             52.479469           53.023379  ...

   Sleep Patterns_Excessive  Sleep Patterns_Insomnia  Sleep Patterns_Normal  \
0                       0.0                      1.0                    0.0
1                       0.0                      0.0                    1.0
2                       0.0                      1.0                    0.0
3                       0.0                      1.0                    0.0
4                       0.0                      0.0                    1.0

   Education Level_Don't Have  Education Level_High School  \
0                         1.0                          0.0
1                         0.0                          0.0
2                         1.0                          0.0
3                         1.0                          0.0
4                         0.0                          0.0

   Education Level_Postgraduate  Education Level_Undergraduate  \
0                           0.0                            0.0
1                           0.0                            1.0
2                           0.0                            0.0
```

```
3                        0.0                           0.0
4                        0.0                           1.0

   Income Level_High  Income Level_Low  Income Level_Medium
0                0.0               0.0                  1.0
1                0.0               0.0                  1.0
2                0.0               0.0                  1.0
3                0.0               1.0                  0.0
4                1.0               0.0                  0.0

[5 rows x 56 columns]
```

Model Training

```
#Separating dependent variable Age
X = df_encoded.drop('Age (years)', axis=1)
y = df_encoded['Age (years)']
```

```
def calculate_correlations(X, y):
    """
    Calculates the Pearson correlation coefficient between each feature in X and

    Args:
        X (pd.DataFrame): DataFrame containing the features.
        y (pd.Series): Series containing the target variable.

    Returns:
        dict: A dictionary mapping feature names to their correlation coefficient
    """
    correlations = {}
    for col in X.columns:
        corr, _ = pearsonr(X[col], y)  # Using pearsonr from scipy.stats
        correlations[col] = corr
    return correlations
```

```
#Select only the numerical features from X
X_numerical = X[[col for col in X.columns if col in numerical_features]]
correlations = calculate_correlations(X_numerical, y)
```

```
#Sort and display top 10 features most correlated with Age
sorted_correlations = sorted(correlations.items(), key=lambda item: item[1], reve
print("Top 10 most correlated features with Age:")
for feature, corr in sorted_correlations[:10]:
    print(f"{feature}: {corr:.4f}")
```

```
Top 10 most correlated features with Age:
Hearing Ability (dB): 0.7124
Systolic_BP: 0.6461
Diastolic_BP: 0.6111
Cholesterol Level (mg/dL): 0.4324
Blood Glucose Level (mg/dL): 0.4286
```

```
Stress Levels: 0.0291
Height (cm): 0.0203
Sun Exposure: 0.0092
Weight (kg): 0.0025
BMI: -0.0080
```

```
df_encoded = df_encoded.drop(columns=['Blood Pressure (s/d)'])
```

```
X = df_encoded.drop('Age (years)', axis=1)
y = df_encoded['Age (years)']
```

```
#Train Test Split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

#Initializing and train the model
rf_model = RandomForestRegressor(random_state=42)
rf_model.fit(X_train, y_train)

y_pred = rf_model.predict(X_test)
```

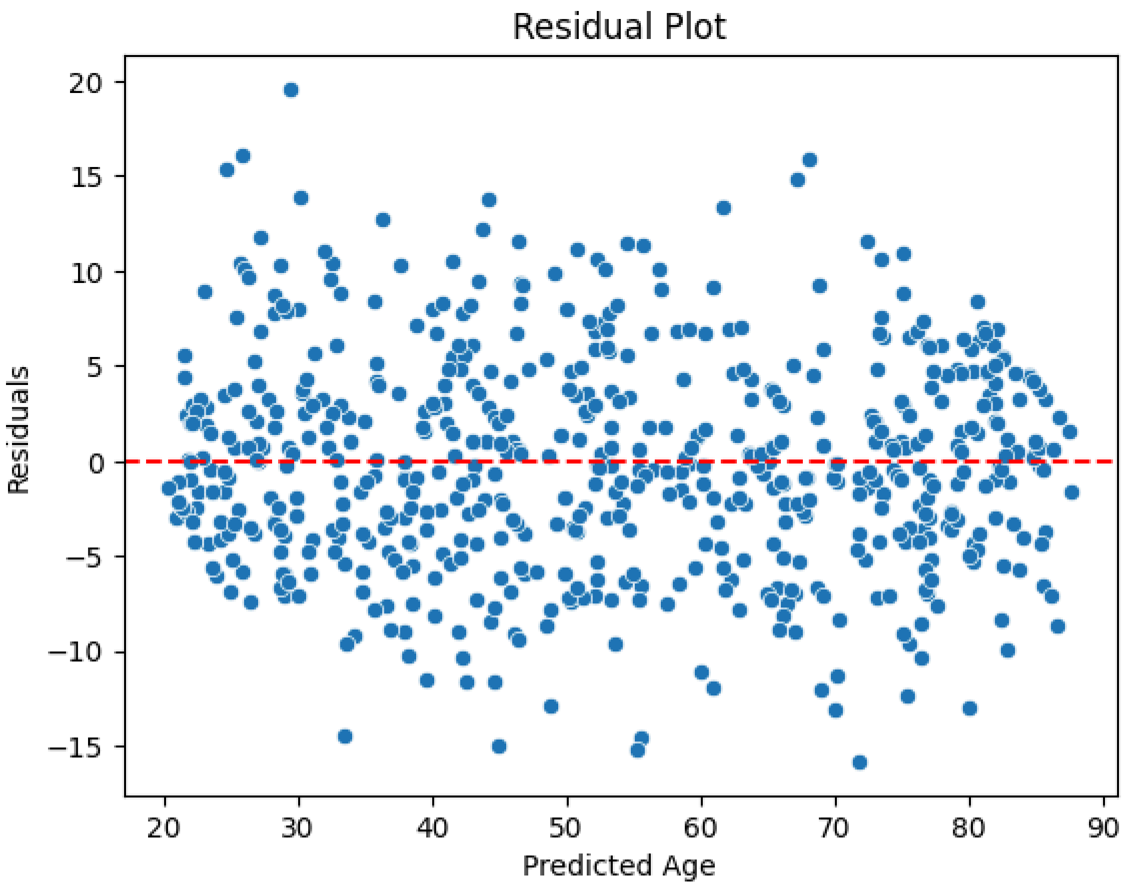
Evaluating the Model

```
#Evaluating Random Forest
from sklearn.metrics import r2_score
rmse = np.sqrt(np.mean((y_test - y_pred)**2))
r2 = r2_score(y_test, y_pred)

print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Root Mean Squared Error (RMSE): 5.66
R² Score: 0.92
```

```
import matplotlib.pyplot as plt
import seaborn as sns

#Residual plot
residuals = y_test - y_pred


sns.scatterplot(x=y_pred, y=residuals)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Predicted Age')
plt.ylabel('Residuals')
```

```
plt.title('Residual Plot')
plt.show()
```

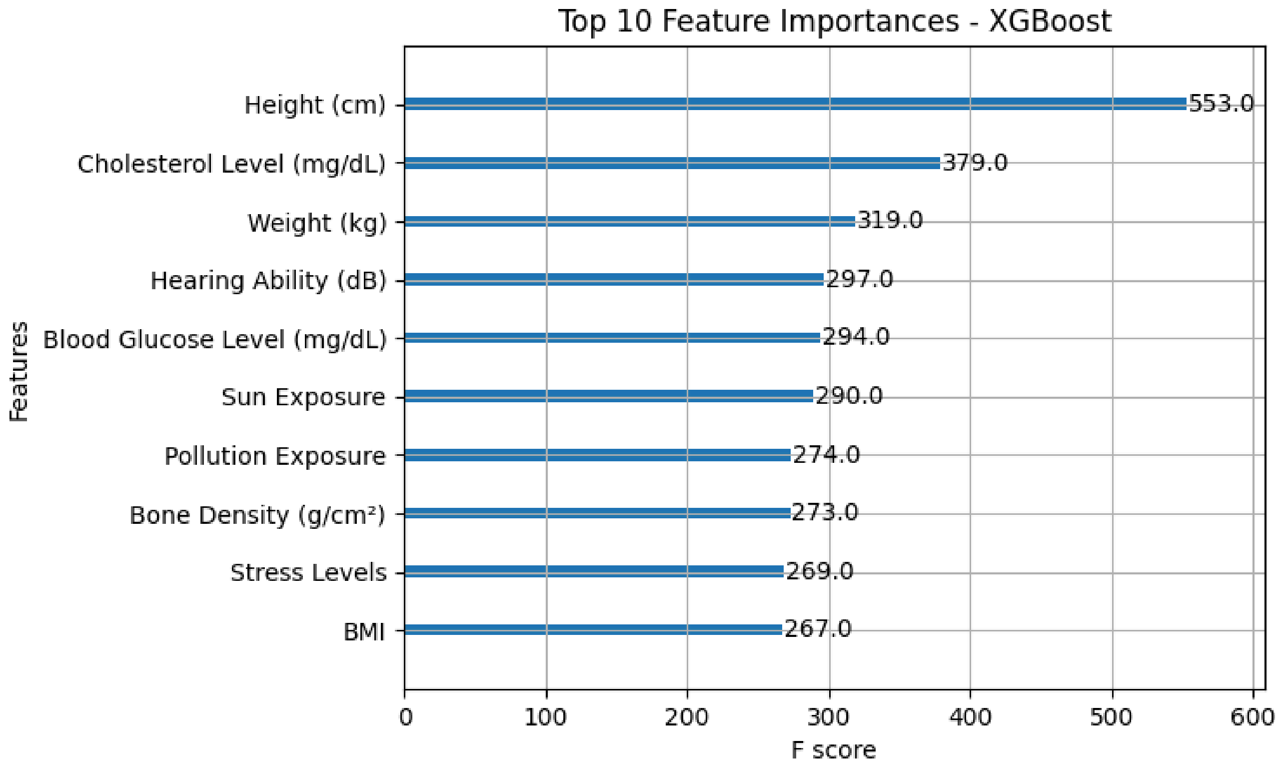



```
from sklearn.linear_model import LinearRegression
from xgboost import XGBRegressor

#Trying Linear Regression
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
lr_pred = lr_model.predict(X_test)
print("Linear Regression R²:", r2_score(y_test, lr_pred))

#Trying XGBoost
xgb_model = XGBRegressor()
xgb_model.fit(X_train, y_train)
xgb_pred = xgb_model.predict(X_test)
print("XGBoost R²:", r2_score(y_test, xgb_pred))
```

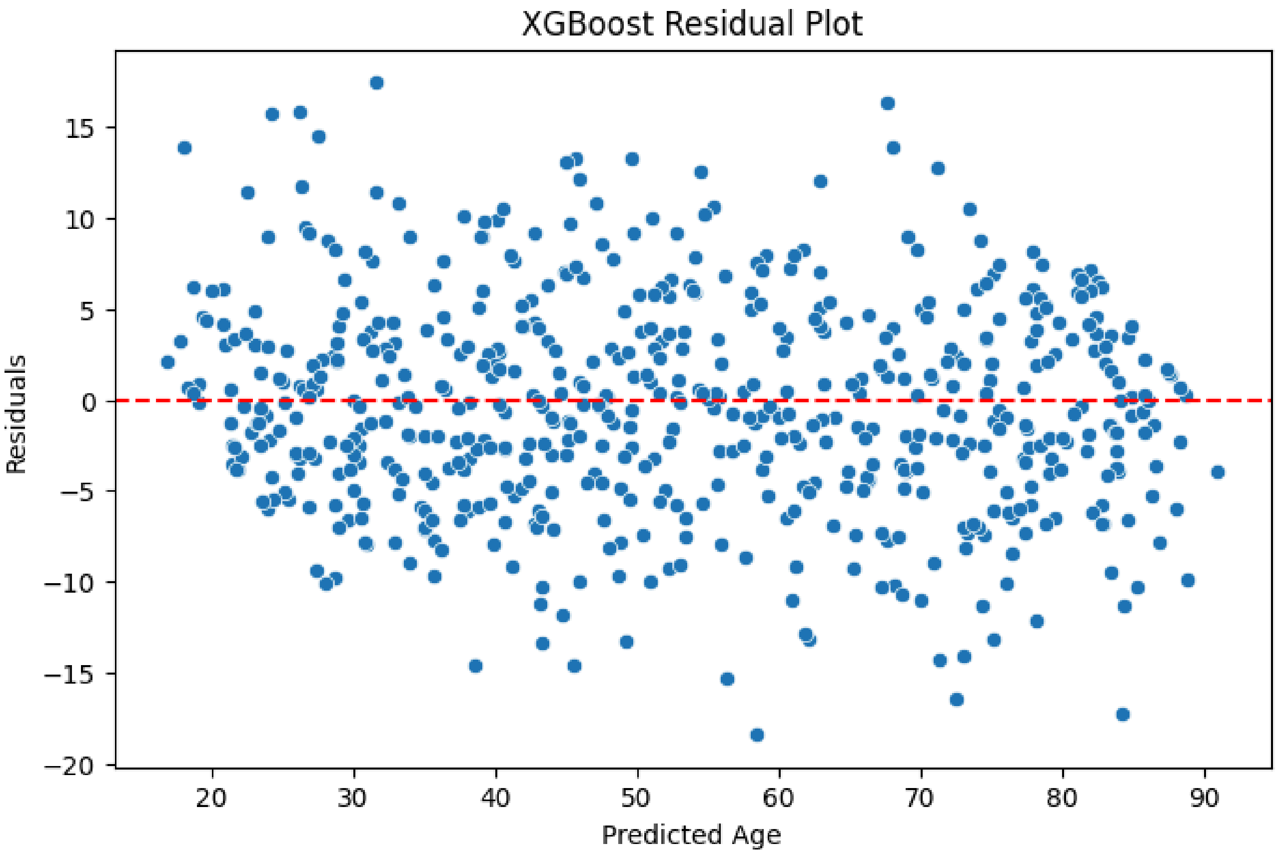
```
Linear Regression R²: 0.93050370856339
XGBoost R²: 0.9159029722213745
```

```
#Feature Importance
import matplotlib.pyplot as plt
from xgboost import plot_importance

plt.figure(figsize=(12, 6))
plot_importance(xgb_model, max_num_features=10)
plt.title("Top 10 Feature Importances - XGBoost")
plt.show()
```

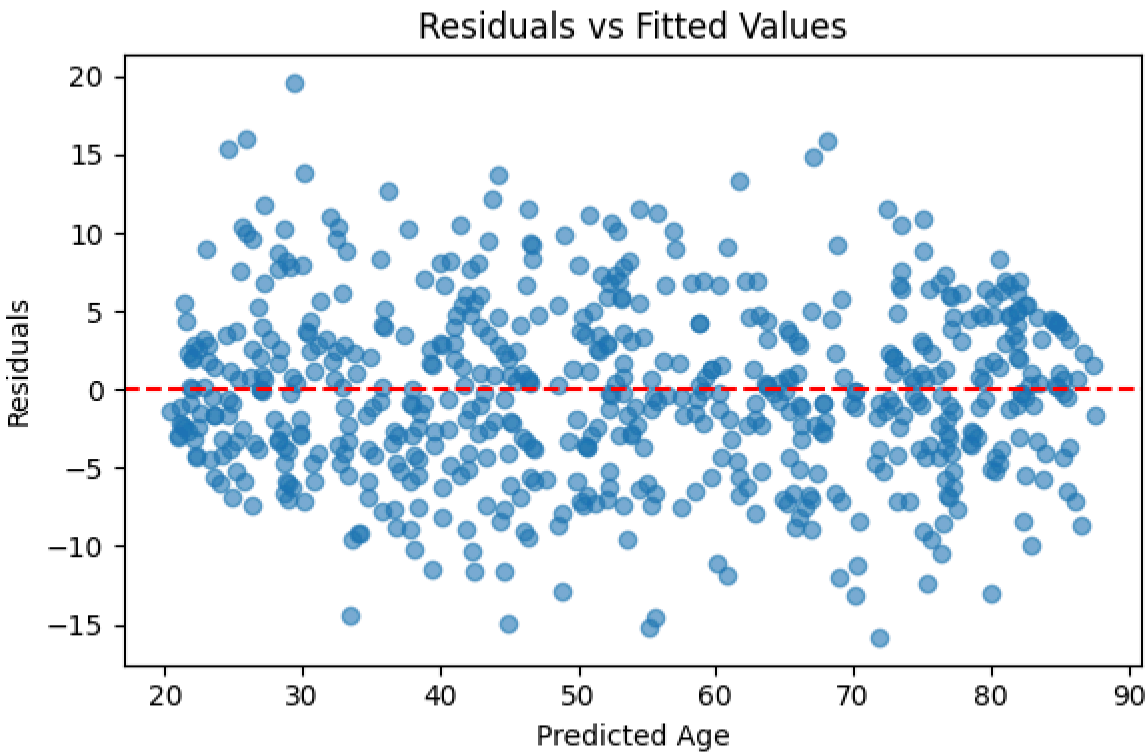
<Figure size 1200x600 with 0 Axes>



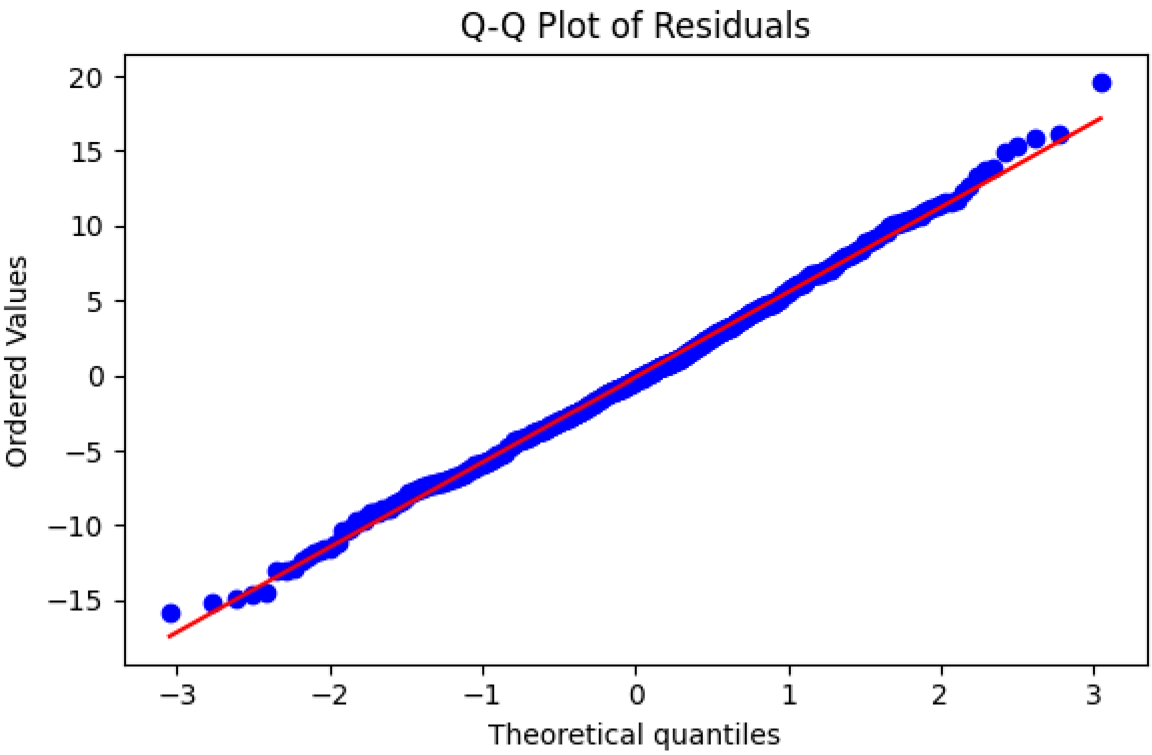

```
#Residual Analysis
residuals = y_test - xgb_pred

plt.figure(figsize=(8, 5))
sns.scatterplot(x=xgb_pred, y=residuals)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Predicted Age')
plt.ylabel('Residuals')
plt.title('XGBoost Residual Plot')
plt.show()
```




```
#Residual v/s fitted
import matplotlib.pyplot as plt

residuals = y_test - y_pred
plt.figure(figsize=(6,4))
plt.scatter(y_pred, residuals, alpha=0.6)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Predicted Age')
plt.ylabel('Residuals')
plt.title('Residuals vs Fitted Values')
plt.tight_layout()
plt.show()
```




```
#QQ plot of residuals
import scipy.stats as stats

plt.figure(figsize=(6,4))
stats.probplot(residuals, dist="norm", plot=plt)
plt.title('Q-Q Plot of Residuals')
plt.tight_layout()
plt.show()
```



Hyperparameter Tuning

```
#Initializing the model
from sklearn.model_selection import GridSearchCV

xgb = XGBRegressor(random_state=42)

# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 4, 5],
    'learning_rate': [0.01, 0.1, 0.2]
}

#GridSearchCV
grid_search = GridSearchCV(
    estimator=xgb,
    param_grid=param_grid,  # Using the defined param_grid
    cv=3,  #3-fold cross-validation
    scoring='neg_mean_squared_error',
    verbose=1,
    n_jobs=-1
)

#Fit to training data
grid_search.fit(X_train, y_train)

#Best model
best_xgb = grid_search.best_estimator_
print("Best Parameters:", grid_search.best_params_)
```

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Best Parameters: {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 100}
```

```
#Predicting with best model
best_pred = best_xgb.predict(X_test)

from sklearn.metrics import mean_squared_error, r2_score
#Calculating RMSE
rmse = np.sqrt(mean_squared_error(y_test, best_pred))
r2 = r2_score(y_test, best_pred)

print(f"Tuned XGBoost RMSE: {rmse:.2f}")
print(f"Tuned XGBoost R² Score: {r2:.2f}")
```

```
Tuned XGBoost RMSE: 5.47
Tuned XGBoost R² Score: 0.93
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

results = pd.DataFrame({
    'Model': ['Linear Regression', 'Random Forest', 'XGBoost (Default)', 'XGBoost
```

```
    'MAE': [
        mean_absolute_error(y_test, lr_pred),
        mean_absolute_error(y_test, y_pred),
        mean_absolute_error(y_test, xgb_pred),
        mean_absolute_error(y_test, best_pred)
    ],

    'MSE': [
        mean_squared_error(y_test, lr_pred),
        mean_squared_error(y_test, y_pred),
        mean_squared_error(y_test, xgb_pred),
        mean_squared_error(y_test, best_pred)
    ],

    'RMSE': [
        np.sqrt(mean_squared_error(y_test, lr_pred)),
        np.sqrt(mean_squared_error(y_test, y_pred)),
        np.sqrt(mean_squared_error(y_test, xgb_pred)),
        np.sqrt(mean_squared_error(y_test, best_pred))
    ],

    'R² Score': [
        r2_score(y_test, lr_pred),
        r2_score(y_test, y_pred),
        r2_score(y_test, xgb_pred),
        r2_score(y_test, best_pred)
    ]
})

#Rounding to 2 decimal places
results = results.round(2)

print(results)
```

```
               Model   MAE    MSE  RMSE  R² Score
0  Linear Regression  4.25  28.48  5.34      0.93
1      Random Forest  4.49  32.01  5.66      0.92
2  XGBoost (Default)  4.67  34.46  5.87      0.92
3    XGBoost (Tuned)  4.36  29.91  5.47      0.93
```

Age Predictions

```
#DataFrame of actual vs predicted values
age_predictions = pd.DataFrame({
    'Actual Age': y_test.values,
    'Predicted Age': best_pred
})

print(age_predictions.head())
```

```
   Actual Age  Predicted Age
0          67      73.300735
```

```
1           59      50.329124
2           52      45.234802
3           67      62.785042
4           49      49.737980
```

```
age_predictions['Absolute Error'] = abs(age_predictions['Actual Age'] - age_predi
print(age_predictions.head())
```

```
   Actual Age  Predicted Age  Absolute Error
0          67      73.300735        6.300735
1          59      50.329124        8.670876
2          52      45.234802        6.765198
3          67      62.785042        4.214958
4          49      49.737980        0.737980
```

Feature Importance

```
#Sorting correlations in descending order (most positive first)
sorted_correlations = sorted(correlations.items(), key=lambda item: abs(item[1]),

#Filter out negative correlations
positive_correlations = [item for item in sorted_correlations if item[1] > 0]

#Get the top 10
top_10_positive = positive_correlations[:10]

print("Top 10 most correlated features with Age (positive):")
for feature, corr in top_10_positive:
    print(f"{feature}: {corr:.4f}")
```

```
Top 10 most correlated features with Age (positive):
Hearing Ability (dB): 0.7124
Systolic_BP: 0.6461
Diastolic_BP: 0.6111
Cholesterol Level (mg/dL): 0.4324
Blood Glucose Level (mg/dL): 0.4286
Stress Levels: 0.0291
Height (cm): 0.0203
Sun Exposure: 0.0092
Weight (kg): 0.0025
```

```
#Feature importance values
importances = best_xgb.feature_importances_
feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importances
})

#Sort and display top 10
top_features = feature_importance_df.sort_values(by='Importance', ascending=False
print("Top 10 Predictive Features:")
```

```
print(top_features)
```

```
Top 10 Predictive Features:
                      Feature  Importance
5          Bone Density (g/cm²)    0.736961
6             Vision Sharpness    0.142290
7          Hearing Ability (dB)    0.016714
12                 Systolic_BP    0.013393
21         Smoking Status_Never    0.010138
13                Diastolic_BP    0.009534
8           Cognitive Function    0.005440
2     Cholesterol Level (mg/dL)    0.004908
4   Blood Glucose Level (mg/dL)    0.004511
20        Smoking Status_Former    0.003365
```

Final Predictions on Test Data

```
import joblib
from xgboost import XGBRegressor

#Training the best model on the full training data
best_xgb = XGBRegressor(**grid_search.best_params_, random_state=42)
best_xgb.fit(X_train, y_train)

#Saving the trained model
joblib.dump(best_xgb, "best_xgb_model.pkl")
```

```
['best_xgb_model.pkl']
```

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder, MinMaxScaler, OneHotEncoder
import joblib

#Loading test data
test_df = pd.read_csv("Test.csv")
test_processed = test_df.copy()

#Splitting Blood Pressure
test_processed[['Systolic_BP', 'Diastolic_BP']] = test_processed['Blood Pressure
test_processed.drop(columns=['Blood Pressure (s/d)'], inplace=True)

#Filling missing categorical values with "Don't Have"
categorical_cols = [
    'Gender', 'Physical Activity Level', 'Smoking Status',
    'Alcohol Consumption', 'Diet', 'Chronic Diseases',
    'Medication Use', 'Family History', 'Mental Health Status',
    'Sleep Patterns', 'Education Level', 'Income Level'
]
for col in categorical_cols:
    test_processed[col] = test_processed[col].fillna("Don't Have")
```

```
#One-Hot Encoding
encoder = OneHotEncoder(handle_unknown='ignore', sparse_output=False)
#Fit the encoder on the categorical columns of the training data (X_train)
encoder.fit(df.loc[:,['Gender','Physical Activity Level','Smoking Status','Alcoho


encoded_features_test = encoder.transform(test_processed.loc[:,['Gender','Physica
encoded_df_test = pd.DataFrame(encoded_features_test, columns=encoder.get_feature
test_processed = test_processed.drop(columns=categorical_cols)
test_processed = pd.concat([test_processed, encoded_df_test], axis=1)

#Ensuring columns are in the same order as the training data
test_processed = test_processed[X_train.columns]


#Loading the trained model
best_xgb = joblib.load("best_xgb_model.pkl")

#Making predictions on the processed test data
test_predictions = best_xgb.predict(test_processed)

#Saving the predictions
submission = pd.DataFrame({'Index': test_df.index, 'Predicted Age': test_predicti
submission.to_csv("final_predicted_ages.csv", index=False)

print("✅ Predictions saved to final_predicted_ages.csv")
submission.head()
```

✅ Predictions saved to final_predicted_ages.csv

	Index	Predicted Age
0	0	85.481438
1	1	72.188004
2	2	74.627487
3	3	49.480972
4	4	77.494354

Next steps: Generate code with submission | View recommended plots | New interactive sheet

```
# Loading the data
test_df = pd.read_csv("Test.csv")
test_processed = test_df.copy()

#Splitting Blood Pressure
test_processed[['Systolic_BP', 'Diastolic_BP']] = test_processed['Blood Pressure
test_processed.drop(columns=['Blood Pressure (s/d)'], inplace=True)

#Filling missing categorical values with "Don't Have"
categorical_cols = [
```

```
    'Gender', 'Physical Activity Level', 'Smoking Status',
    'Alcohol Consumption', 'Diet', 'Chronic Diseases',
    'Medication Use', 'Family History', 'Mental Health Status',
    'Sleep Patterns', 'Education Level', 'Income Level'
]
for col in categorical_cols:
    test_processed[col] = test_processed[col].fillna("Don't Have")
```

```
print(test_processed.head())
```

```
   Gender  Height (cm)  Weight (kg)  Cholesterol Level (mg/dL)        BMI  \
0    Male   171.148359    86.185197                 259.465814  29.423017
1    Male   172.946206    79.641937                 263.630292  26.626847
2  Female   155.945488    49.167058                 207.846206  20.217553
3  Female   169.078298    56.017921                 253.283779  19.595270
4  Female   163.758355    73.966304                 236.119899  27.582078

   Blood Glucose Level (mg/dL)  Bone Density (g/cm²)  Vision Sharpness  \
0                   157.652848              0.132868          0.200000
1                   118.507805              0.629534          0.267312
2                   143.587550              0.473487          0.248667
3                   137.448581              1.184315          0.513818
4                   145.328695              0.434562          0.306864

   Hearing Ability (dB) Physical Activity Level  ... Cognitive Function  \
0             58.786198                Moderate  ...          44.059172
1             54.635270                     Low  ...          45.312298
2             54.564632                Moderate  ...          56.246991
3             79.722963                Moderate  ...          55.196092
4             52.479469                     Low  ...          53.023379

  Mental Health Status Sleep Patterns Stress Levels Pollution Exposure  \
0                 Good       Insomnia      2.797064           5.142344
1                 Good         Normal      9.339930           7.272720
2                 Poor       Insomnia      9.234637           8.500386
3                 Poor       Insomnia      4.693446           7.555511
4                 Good         Normal      4.038537           9.429097

  Sun Exposure  Education Level Income Level Systolic_BP  Diastolic_BP
0     7.108975       Don't Have       Medium       151.0         109.0
1     3.918489    Undergraduate       Medium       134.0         112.0
2     5.393408       Don't Have       Medium       160.0         101.0
3     2.745578       Don't Have          Low       133.0          94.0
4     3.878435    Undergraduate         High       170.0         106.0

[5 rows x 26 columns]
```

```
encoder = OneHotEncoder(handle_unknown='ignore', sparse_output=False)
#Fit the encoder on the categorical columns of the training data (X_train)
encoder.fit(df.loc[:,['Gender','Physical Activity Level','Smoking Status','Alcoho
```

```
▾ OneHotEncoder
OneHotEncoder(handle_unknown='ignore', sparse_output=False)
```

```
encoded_features_test = encoder.transform(test_df.loc[:,['Gender','Physical Activ
encoded_df_test = pd.DataFrame(encoded_features_test, columns=encoder.get_feature
test_processed = test_processed.drop(columns=categorical_cols)
test_processed = pd.concat([test_processed, encoded_df_test], axis=1)

#Ensuring columns are in the same order as the training data
test_processed = test_processed[X_train.columns]



#Loading the trained model
best_xgb = joblib.load("best_xgb_model.pkl")

#Making predictions on the processed test data
test_predictions = best_xgb.predict(test_processed)

submission = pd.DataFrame({'Index': test_df.index, 'Predicted Age': test_predicti
submission.to_csv("final_predicted_ages.csv", index=False)

print("✅ Predictions saved to final_predicted_ages.csv")
submission.head()
```

✅ Predictions saved to final_predicted_ages.csv

	Index	Predicted Age
0	0	85.611786
1	1	72.188004
2	2	74.627487
3	3	49.611320
4	4	77.494354

Next steps: Generate code with submission View recommended plots New interactive sheet

Merging Predicted Age with Test Data

```
test_with_predictions = test_df.drop(columns=['Blood Pressure (s/d)']).copy()

#Filling missing categorical values with "Don't Have"
categorical_cols = [
    'Gender', 'Physical Activity Level', 'Smoking Status',
    'Alcohol Consumption', 'Diet', 'Chronic Diseases',
    'Medication Use', 'Family History', 'Mental Health Status',
    'Sleep Patterns', 'Education Level', 'Income Level'
]
for col in categorical_cols:
    test_with_predictions[col] = test_with_predictions[col].fillna("Don't Have")

#Adding Systolic_BP and Diastolic_BP columns from test_processed
test_with_predictions['Systolic_BP'] = test_processed['Systolic_BP']
```

```
test_with_predictions['Diastolic_BP'] = test_processed['Diastolic_BP']

#Adding predicted ages
test_with_predictions['Predicted Age'] = test_predictions
```

```
test_with_predictions.head()
```

	Gender	Height (cm)	Weight (kg)	Cholesterol Level (mg/dL)	BMI	Blood Glucose Level (mg/dL)	Bone Density (g/cm²)	Vi Sharp
0	Male	171.148359	86.185197	259.465814	29.423017	157.652848	0.132868	0.2C
1	Male	172.946206	79.641937	263.630292	26.626847	118.507805	0.629534	0.26
2	Female	155.945488	49.167058	207.846206	20.217553	143.587550	0.473487	0.24
3	Female	169.078298	56.017921	253.283779	19.595270	137.448581	1.184315	0.51
4	Female	163.758355	73.966304	236.119899	27.582078	145.328695	0.434562	0.3C

5 rows × 27 columns

```
#Saving the updated DataFrame to a new CSV file
test_with_predictions.to_csv("Test_Updated.csv", index=False)
print("✅ Test data with predictions saved to Test_Updated.csv")
```

```
✅ Test data with predictions saved to Test_Updated.csv
```

Summary

In this project, we built a predictive model to estimate human age based on health and lifestyle indicators using machine learning techniques. After preprocessing, feature engineering, and model selection, the tuned XGBoost Regressor emerged as the best-performing model with an RMSE of 5.47, MAE of 4.36, and an R^2 score of 0.93, indicating strong predictive accuracy. The most influential features in predicting age were Bone Density (g/cm²), Vision Sharpness, and Hearing Ability (dB), as identified by both model-based and permutation importance. The model was then successfully applied to a new dataset (Test.csv) to generate age predictions. This analysis demonstrates how physiological and behavioral data can be effectively used to estimate age, with potential applications in preventative healthcare, wellness analytics, and insurance risk profiling.

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