How can life expectancy be improved through targeted interventions in developing and developed countries

```
# Basic Libraries
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt # we only need pyplot
sb.set() # set the default Seaborn style for graphics
# Import essential models and functions from sklearn
from sklearn.model_selection import train_test_split as split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeRegressor

import xgboost as xgb

lifedata = pd.read_csv(r"Life Expectancy Data.csv")
lifedata.head()
```

```
       Country  Year      Status  Life expectancy   Adult Mortality  \
0  Afghanistan  2015  Developing              65.0            263.0
1  Afghanistan  2014  Developing              59.9            271.0
2  Afghanistan  2013  Developing              59.9            268.0
3  Afghanistan  2012  Developing              59.5            272.0
4  Afghanistan  2011  Developing              59.2            275.0

   infant deaths  Alcohol  percentage expenditure  Hepatitis B
Measles   ...  \
0             62     0.01               71.279624         65.0
1154  ...
1             64     0.01               73.523582         62.0
492  ...
2             66     0.01               73.219243         64.0
430  ...
3             69     0.01               78.184215         67.0
2787  ...
4             71     0.01                7.097109         68.0
3013  ...

   Polio  Total expenditure  Diphtheria    HIV/AIDS         GDP
Population  \
0    6.0               8.16         65.0        0.1  584.259210
33736494.0
1   58.0               8.18         62.0        0.1  612.696514
327582.0
```

```
2   62.0                  8.13          64.0         0.1  631.744976
31731688.0
3   67.0                  8.52          67.0         0.1  669.959000
3696958.0
4   68.0                  7.87          68.0         0.1   63.537231
2978599.0

    thinness  1-19 years   thinness 5-9 years  \
0                   17.2                 17.3
1                   17.5                 17.5
2                   17.7                 17.7
3                   17.9                 18.0
4                   18.2                 18.2

   Income composition of resources  Schooling
0                            0.479       10.1
1                            0.476       10.0
2                            0.470        9.9
3                            0.463        9.8
4                            0.454        9.5

[5 rows x 22 columns]
```

remove data under "Schooling", " Income composition of resources", "under-five deaths" that have value "0"

remove population data <20000

replace empty values with median of status. (developing countries with empty values replaced with developing countries median, developed countries with empty values replaced with developed countries median)

```
lifedata = lifedata[
    (lifedata["Income composition of resources"] != 0) &
    (lifedata["under-five deaths "] != 0) &
    (lifedata["Schooling"] != 0)
]

lifedata = lifedata[lifedata["Population"] >= 20000]


# Identify numeric columns in your DataFrame
numeric_cols = lifedata.select_dtypes(include=[np.number]).columns

# Group by 'Status' and fill missing numeric values with the median
```

```
for each group
lifedata[numeric_cols] = lifedata.groupby('Status')
[numeric_cols].transform(lambda x: x.fillna(x.median()))
```

remove unnecessary columns (see google doc for reason)

```
filtered_data1 = lifedata.drop(columns=['GDP','infant
deaths','percentage expenditure', ' BMI '])
filtered_data1.head()
```

```
       Country  Year      Status  Life expectancy   Adult Mortality
Alcohol  \
0  Afghanistan  2015  Developing              65.0            263.0
0.01
1  Afghanistan  2014  Developing              59.9            271.0
0.01
2  Afghanistan  2013  Developing              59.9            268.0
0.01
3  Afghanistan  2012  Developing              59.5            272.0
0.01
4  Afghanistan  2011  Developing              59.2            275.0
0.01

   Hepatitis B  Measles   under-five deaths   Polio  Total expenditure
\
0         65.0     1154                  83    6.0               8.16

1         62.0      492                  86   58.0               8.18

2         64.0      430                  89   62.0               8.13

3         67.0     2787                  93   67.0               8.52

4         68.0     3013                  97   68.0               7.87


   Diphtheria    HIV/AIDS  Population   thinness  1-19 years  \
0        65.0         0.1  33736494.0                   17.2
1        62.0         0.1    327582.0                   17.5
2        64.0         0.1  31731688.0                   17.7
3        67.0         0.1   3696958.0                   17.9
4        68.0         0.1   2978599.0                   18.2

    thinness 5-9 years  Income composition of resources  Schooling
0                 17.3                            0.479       10.1
1                 17.5                            0.476       10.0
2                 17.7                            0.470        9.9
3                 18.0                            0.463        9.8
4                 18.2                            0.454        9.5
```

Country : Name of the country
Year : Year of the observation
Status : Developed or Developing status of the country
Life expectancy : Life Expectancy in years
Adult Mortality : Adult mortality rate (probability of dying between age 15 and 60 per 1000 population)
Alcohol : Recorded per capita (age 15+) alcohol consumption in litres of pure alcohol
Hepatitis B : Hepatitis B immunization coverage among 1-year-olds (%)
Measles : Reported cases of measles per 1000 population
under-five deaths : Number of under-five deaths per 1000 population
Polio : Polio immunization coverage among 1-year-olds (%)
Total expenditure : Government health expenditure as a percentage of total government expenditure
Diphtheria : DTP3 immunization coverage among 1-year-olds (%)
HIV/AIDS : Deaths per 1000 live births due to HIV/AIDS (ages 0–4 years)
Population : Total population of the country

Income composition of resources : Human Development Index in terms of income composition of resources (index ranging from 0 to 1)
Schooling : Number of years of Schooling(years)
thinness 1-19 years : Prevalence of thinness among children and adolescents for Age 10 to 19 (%)
thinness 5-9 years : Prevalence of thinness among children for Age 5 to 9(%)

exploratory analysis

```
print("Data type : ", type(filtered_data1))
print("Data dims : ", filtered_data1.shape)
```

```
Data type :  <class 'pandas.core.frame.DataFrame'>
Data dims :  (1577, 18)
```

```
print(filtered_data1.dtypes)
```

```
Country                                    object
Year                                        int64
Status                                     object
Life expectancy                           float64
Adult Mortality                           float64
Alcohol                                   float64
Hepatitis B                               float64
Measles                                     int64
under-five deaths                           int64
Polio                                     float64
Total expenditure                         float64
Diphtheria                                float64
 HIV/AIDS                                 float64
Population                                float64
 thinness  1-19 years                     float64
 thinness 5-9 years                       float64
```

```
Income composition of resources    float64
Schooling                          float64
dtype: object
```

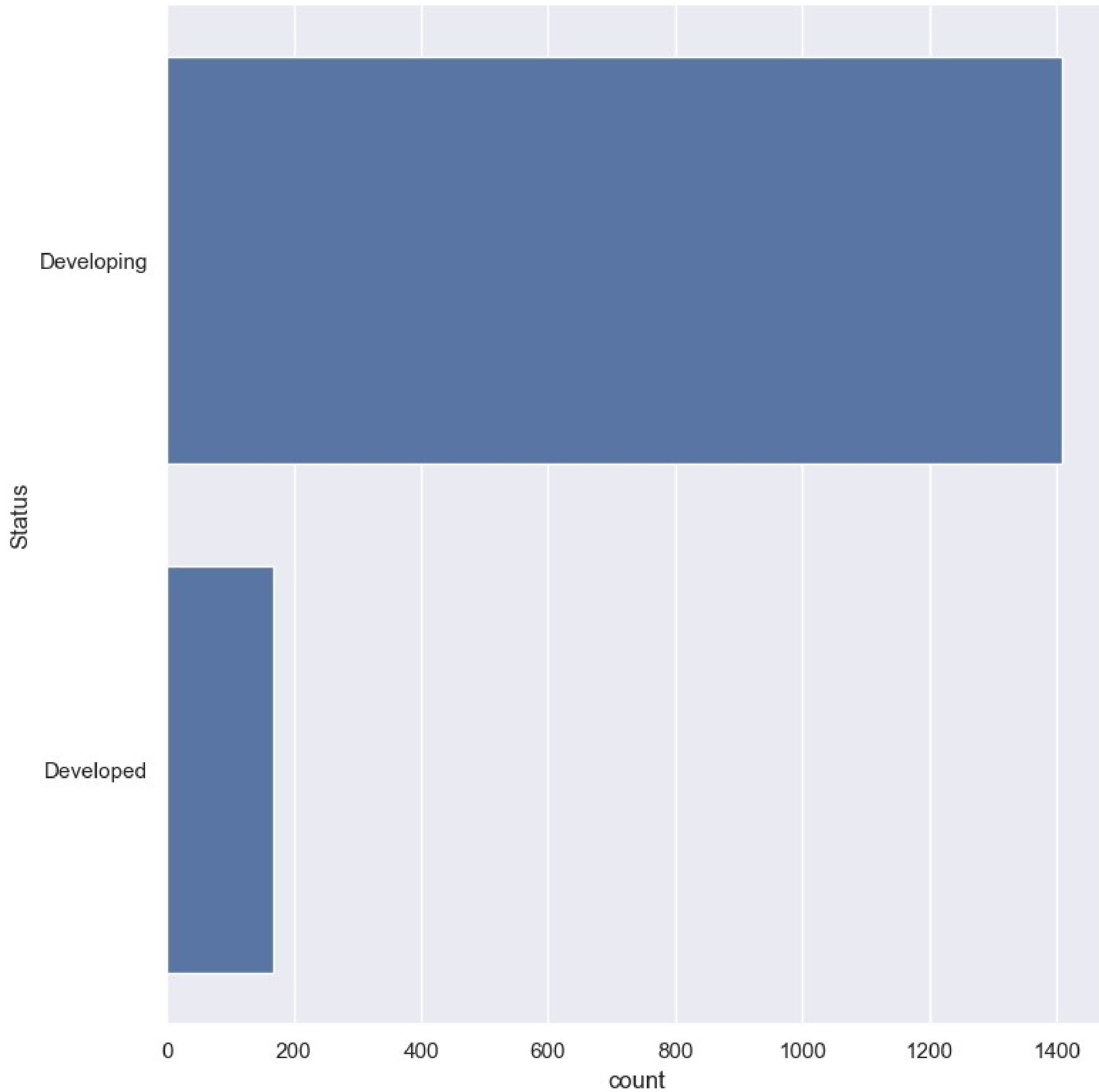
```
filtered_data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1577 entries, 0 to 2937
Data columns (total 18 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   Country                          1577 non-null   object
 1   Year                             1577 non-null   int64
 2   Status                           1577 non-null   object
 3   Life expectancy                  1577 non-null   float64
 4   Adult Mortality                  1577 non-null   float64
 5   Alcohol                          1577 non-null   float64
 6   Hepatitis B                      1577 non-null   float64
 7   Measles                          1577 non-null   int64
 8   under-five deaths                1577 non-null   int64
 9   Polio                            1577 non-null   float64
 10  Total expenditure                1577 non-null   float64
 11  Diphtheria                       1577 non-null   float64
 12   HIV/AIDS                        1577 non-null   float64
 13  Population                       1577 non-null   float64
 14   thinness  1-19 years            1577 non-null   float64
 15   thinness 5-9 years              1577 non-null   float64
 16  Income composition of resources  1577 non-null   float64
 17  Schooling                        1577 non-null   float64
dtypes: float64(13), int64(3), object(2)
memory usage: 234.1+ KB
```

```
print(filtered_data1["Status"].value_counts())
sb.catplot(y = "Status", data = filtered_data1, kind = "count", height
= 8)
```

```
Status
Developing    1410
Developed      167
Name: count, dtype: int64
```

```
<seaborn.axisgrid.FacetGrid at 0x1680f0830>
```




```
# Extract only the numeric data variables
numeric_data = pd.DataFrame(filtered_data1[["Life expectancy ","Adult
Mortality", "Alcohol", "Hepatitis B", "Measles ", "under-five deaths
", "Polio", "Total expenditure", "Diphtheria ", " HIV/AIDS",
"Population", "Income composition of resources", "Schooling", "
thinness  1-19 years", " thinness 5-9 years"]])

# Summary Statistics for all Variables
filtered_data1.describe().round(2)

          Year  Life expectancy   Adult Mortality  Alcohol  Hepatitis
B  \
count  1577.00          1577.00          1577.00  1577.00
```

```
1577.00
mean   2007.63             66.64            191.34     4.09
79.43
std       4.59              9.87            138.32     3.69
24.00
min    2000.00             36.30              1.00     0.01
2.00
25%    2004.00             58.90             86.00     0.76
76.00
50%    2008.00             67.80            163.00     2.87
87.00
75%    2012.00             74.20            273.00     6.74
95.00
max    2015.00             89.00            723.00    17.31
99.00

         Measles   under-five deaths     Polio  Total expenditure
Diphtheria   \
count    1577.00             1577.00  1577.00            1577.00
1577.00
mean     2976.49               62.96    78.60               5.83
79.27
std     10489.49              206.64    25.05               2.21
24.46
min         0.00                1.00     3.00               0.37
2.00
25%         0.00                3.00    72.00               4.37
73.00
50%        63.00               12.00    88.00               5.58
88.00
75%       982.00               49.00    96.00               7.19
96.00
max    131441.00             2500.00    99.00              14.39
99.00

         HIV/AIDS    Population   thinness  1-19 years   thinness 5-9
years  \
count    1577.00  1.577000e+03                1577.00
1577.00
mean        2.72  1.768839e+07                   5.42
5.52
std         6.38  7.275104e+07                   4.73
4.83
min         0.10  2.127400e+04                   0.50
0.40
25%         0.10  6.789140e+05                   1.90
1.90
50%         0.20  2.728777e+06                   3.90
4.10
```

```
75%          2.10  1.355847e+07                        7.80
7.90
max         50.60  1.293859e+09                       27.70
28.60

       Income composition of resources  Schooling
count                          1577.00    1577.00
mean                              0.61      11.31
std                               0.16       3.15
min                               0.25       2.80
25%                               0.46       9.20
50%                               0.62      11.40
75%                               0.73      13.30
max                               0.94      20.70
```

only have developing countries in dataset first

```
developing_data = filtered_data1[filtered_data1['Status'] ==
'Developing']
developing_data.head()
```

```
       Country  Year      Status  Life expectancy   Adult Mortality
Alcohol  \
0  Afghanistan  2015  Developing              65.0            263.0
0.01
1  Afghanistan  2014  Developing              59.9            271.0
0.01
2  Afghanistan  2013  Developing              59.9            268.0
0.01
3  Afghanistan  2012  Developing              59.5            272.0
0.01
4  Afghanistan  2011  Developing              59.2            275.0
0.01

   Hepatitis B  Measles   under-five deaths   Polio  Total expenditure
\
0         65.0     1154                  83     6.0               8.16

1         62.0      492                  86    58.0               8.18

2         64.0      430                  89    62.0               8.13

3         67.0     2787                  93    67.0               8.52

4         68.0     3013                  97    68.0               7.87


   Diphtheria    HIV/AIDS  Population   thinness  1-19 years  \
0        65.0         0.1  33736494.0                    17.2
1        62.0         0.1    327582.0                    17.5
```

2	64.0	0.1	31731688.0	17.7
3	67.0	0.1	3696958.0	17.9
4	68.0	0.1	2978599.0	18.2

	thinness 5-9 years	Income composition of resources	Schooling
0	17.3	0.479	10.1
1	17.5	0.476	10.0
2	17.7	0.470	9.9
3	18.0	0.463	9.8
4	18.2	0.454	9.5

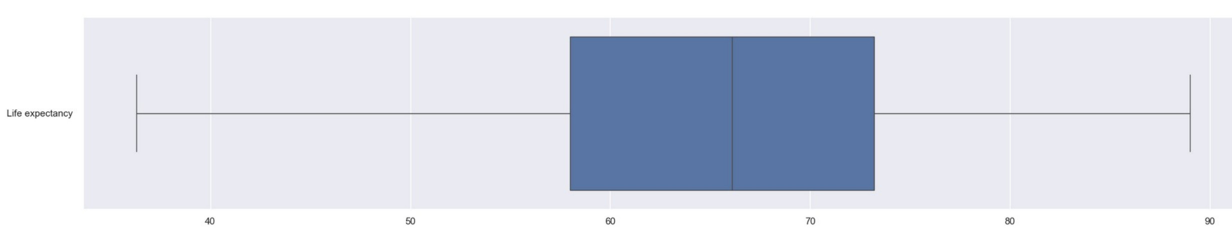
make life expectancy dataframe and explore

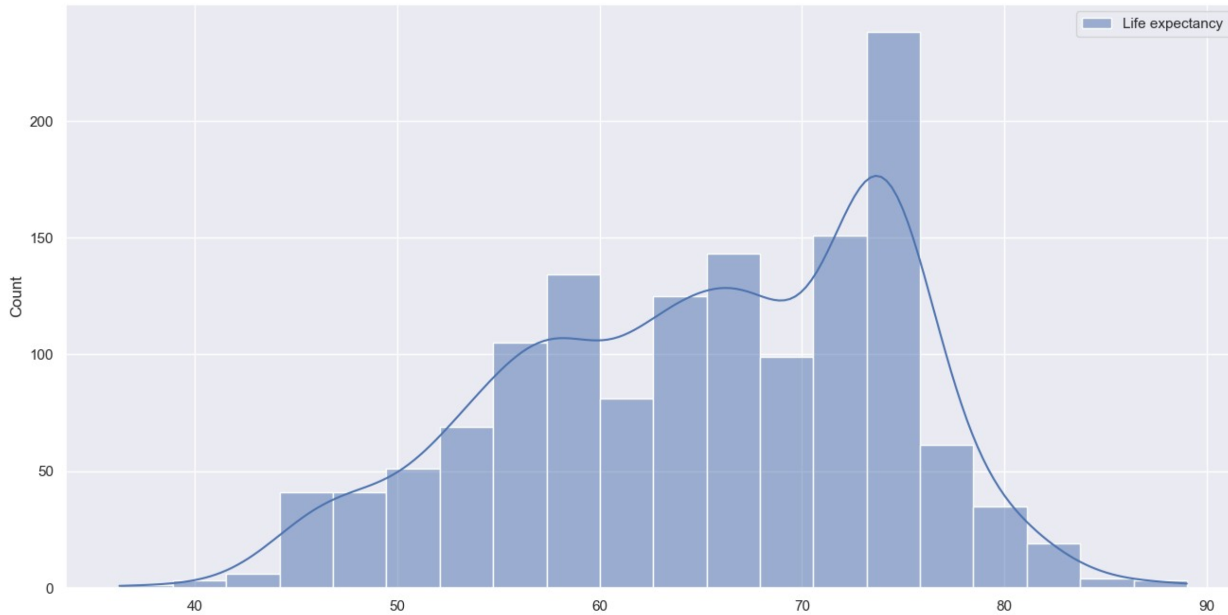
```
lifeex = pd.DataFrame(developing_data['Life expectancy '])
lifeex.describe()
```

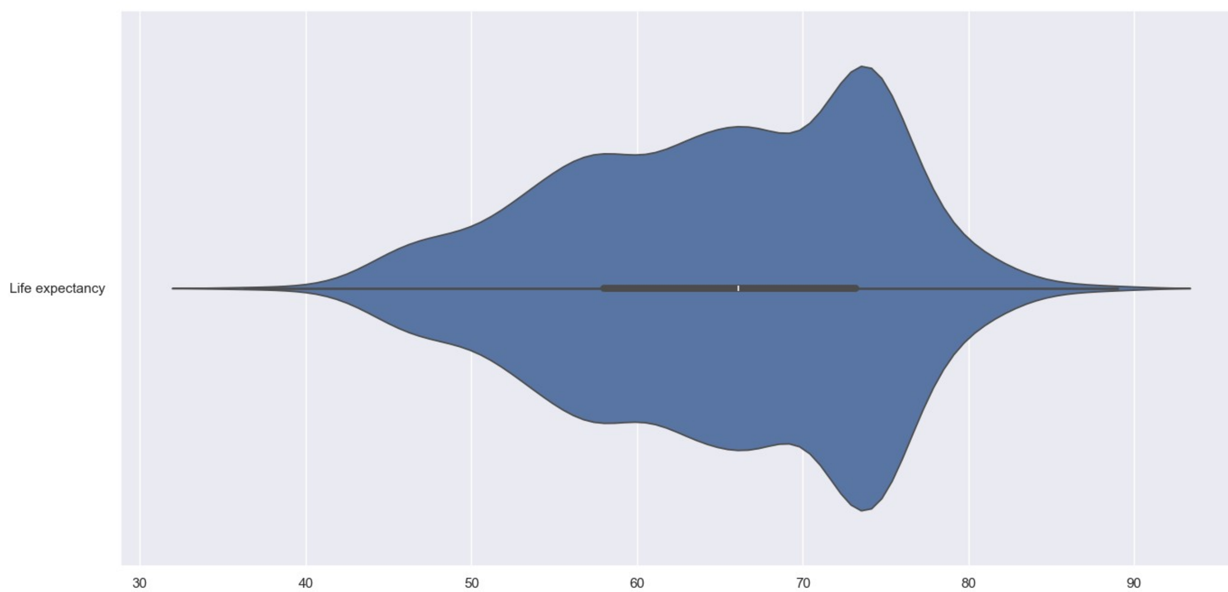
	Life expectancy
count	1410.000000
mean	65.181418
std	9.313073
min	36.300000
25%	58.000000
50%	66.100000
75%	73.200000
max	89.000000

```
f = plt.figure(figsize=(24, 4))
sb.boxplot(data = lifeex, orient = "h")

f = plt.figure(figsize=(16, 8))
sb.histplot(data = lifeex, kde = True)

f = plt.figure(figsize=(16, 8))
sb.violinplot(data = lifeex, orient = "h")
```

```
<Axes: >
```







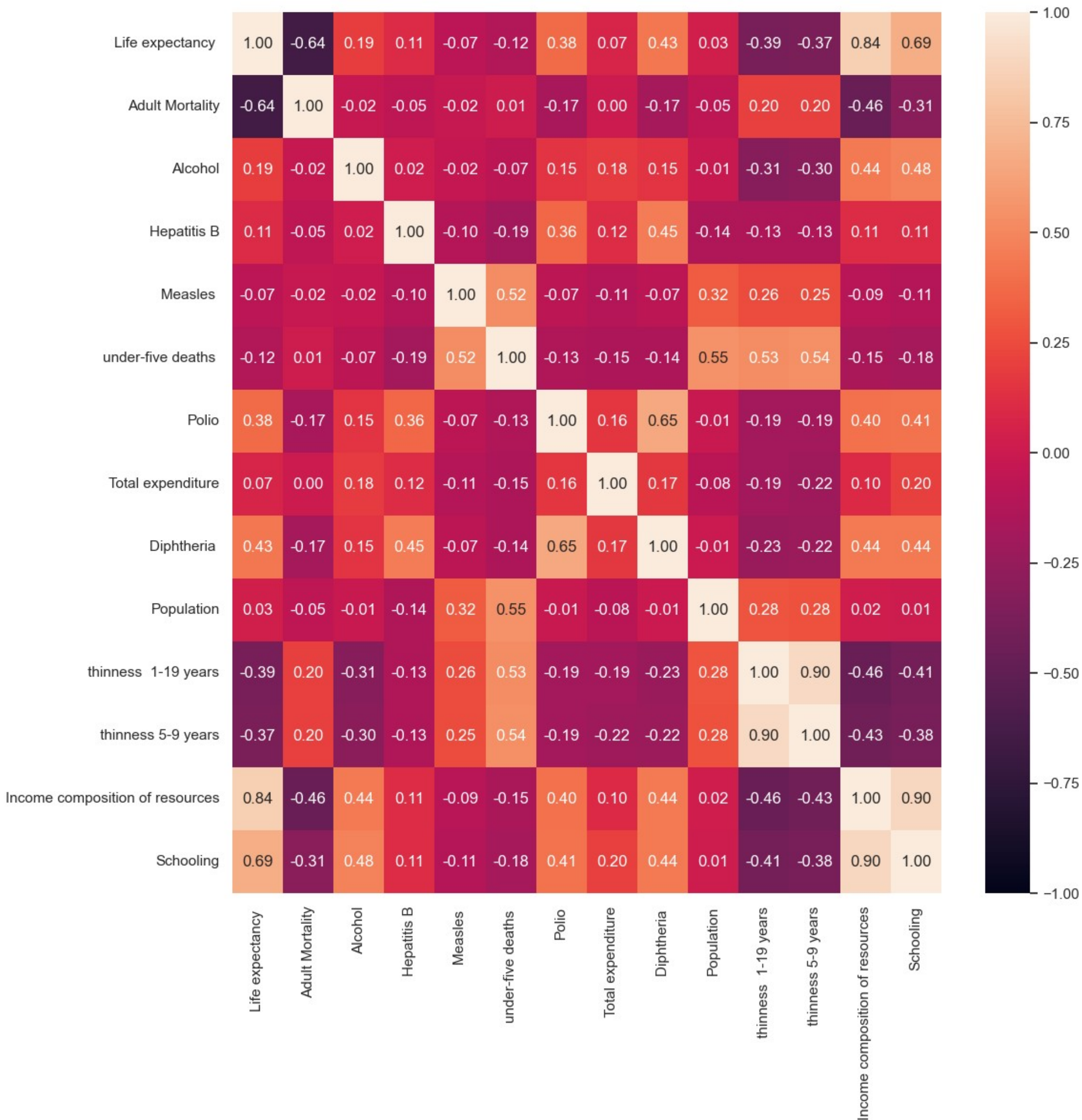

```
filtered_data2 = developing_data.drop(columns=["Country", "Year",
"Status", " HIV/AIDS"])
filtered_data2.corr()

                                 Life expectancy   Adult Mortality
Alcohol  \
Life expectancy                         1.000000         -0.642059
0.188488
Adult Mortality                        -0.642059          1.000000 -
0.015995
Alcohol                                 0.188488         -0.015995
1.000000
```

```
Hepatitis B                                    0.108088        -0.054979
0.020245
Measles                                       -0.071399        -0.017491 -
0.024891
under-five deaths                             -0.118896         0.014595 -
0.069674
Polio                                          0.379388        -0.168670
0.148610
Total expenditure                              0.074603         0.001391
0.183653
Diphtheria                                     0.430649        -0.174167
0.149995
Population                                     0.034843        -0.054840 -
0.010831
 thinness  1-19 years                         -0.386104         0.196339 -
0.314620
 thinness 5-9 years                           -0.374413         0.203203 -
0.297473
Income composition of resources                0.844645        -0.457043
0.441855
Schooling                                      0.685490        -0.310592
0.483397

                                 Hepatitis B  Measles   under-five
deaths   \
Life expectancy                     0.108088 -0.071399            -
0.118896
Adult Mortality                    -0.054979 -0.017491
0.014595
Alcohol                             0.020245 -0.024891            -
0.069674
Hepatitis B                         1.000000 -0.102421            -
0.186920
Measles                            -0.102421  1.000000
0.523556
under-five deaths                  -0.186920  0.523556
1.000000
Polio                               0.360090 -0.065574            -
0.130554
Total expenditure                   0.116292 -0.107237            -
0.145145
Diphtheria                          0.454874 -0.070160            -
0.144816
Population                         -0.140113  0.318614
0.549169
 thinness  1-19 years              -0.128790  0.257432
0.528847
 thinness 5-9 years                -0.134813  0.254029
0.535401
```

```
Income composition of resources     0.112818 -0.093295           -
0.151828
Schooling                           0.113047 -0.111055           -
0.177378

                                    Polio  Total expenditure
Diphtheria   \
Life expectancy                  0.379388           0.074603
0.430649
Adult Mortality                 -0.168670           0.001391    -
0.174167
Alcohol                          0.148610           0.183653
0.149995
Hepatitis B                      0.360090           0.116292
0.454874
Measles                         -0.065574          -0.107237    -
0.070160
under-five deaths               -0.130554          -0.145145    -
0.144816
Polio                            1.000000           0.160452
0.654507
Total expenditure                0.160452           1.000000
0.171496
Diphtheria                       0.654507           0.171496
1.000000
Population                      -0.013916          -0.079643    -
0.005710
 thinness  1-19 years           -0.189257          -0.192975    -
0.228093
 thinness 5-9 years             -0.192333          -0.217726    -
0.221212
Income composition of resources  0.401045           0.096521
0.440843
Schooling                        0.407512           0.197680
0.440528

                                 Population   thinness  1-19 years  \
Life expectancy                    0.034843             -0.386104
Adult Mortality                   -0.054840              0.196339
Alcohol                           -0.010831             -0.314620
Hepatitis B                       -0.140113             -0.128790
Measles                            0.318614              0.257432
under-five deaths                  0.549169              0.528847
Polio                             -0.013916             -0.189257
Total expenditure                 -0.079643             -0.192975
Diphtheria                        -0.005710             -0.228093
Population                         1.000000              0.283081
 thinness  1-19 years              0.283081              1.000000
 thinness 5-9 years                0.279258              0.899908
```

```
Income composition of resources    0.024948             -0.456182
Schooling                          0.009833             -0.405404

                                 thinness 5-9 years  \
Life expectancy                           -0.374413
Adult Mortality                            0.203203
Alcohol                                   -0.297473
Hepatitis B                               -0.134813
Measles                                    0.254029
under-five deaths                          0.535401
Polio                                     -0.192333
Total expenditure                         -0.217726
Diphtheria                                -0.221212
Population                                 0.279258
 thinness  1-19 years                      0.899908
 thinness 5-9 years                        1.000000
Income composition of resources           -0.428130
Schooling                                 -0.383531

                                 Income composition of resources
Schooling
Life expectancy                                         0.844645
0.685490
Adult Mortality                                        -0.457043  -
0.310592
Alcohol                                                 0.441855
0.483397
Hepatitis B                                             0.112818
0.113047
Measles                                                -0.093295  -
0.111055
under-five deaths                                      -0.151828  -
0.177378
Polio                                                   0.401045
0.407512
Total expenditure                                       0.096521
0.197680
Diphtheria                                              0.440843
0.440528
Population                                              0.024948
0.009833
 thinness  1-19 years                                  -0.456182  -
0.405404
 thinness 5-9 years                                    -0.428130  -
0.383531
Income composition of resources                         1.000000
0.897527
Schooling                                               0.897527
1.000000
```

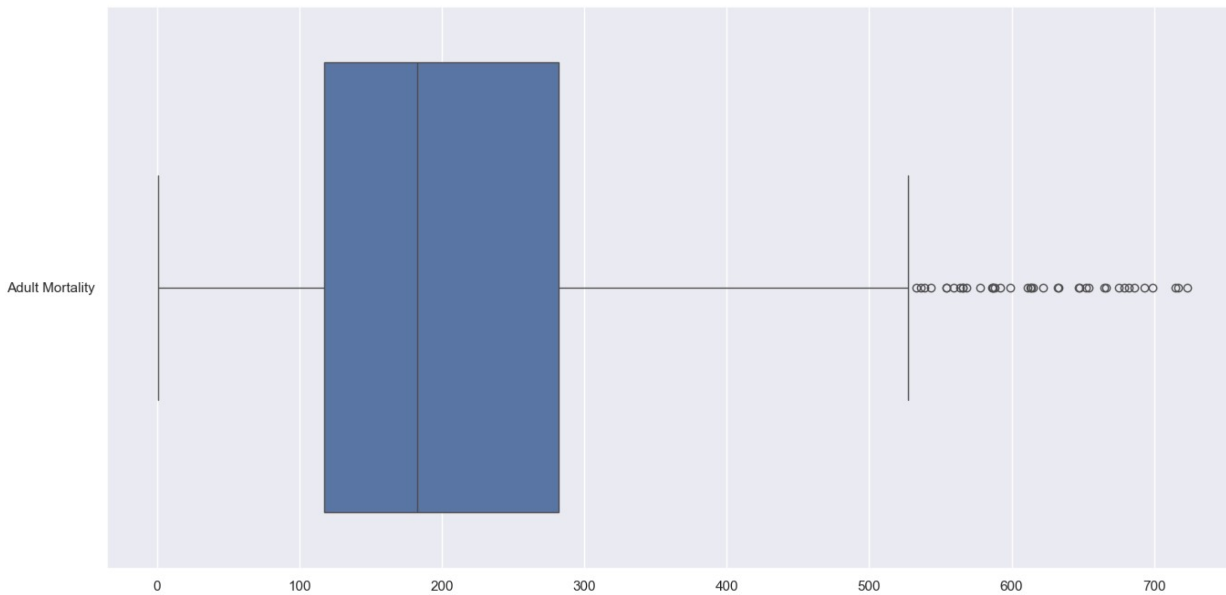
```
f = plt.figure(figsize=(12, 12))
sb.heatmap(filtered_data2.corr(), vmin = -1, vmax = 1, annot = True,
fmt = ".2f")

<Axes: >
```



we group health outcomes (adult mortality, HIV/AIDS), immunization coverage (Polio, Diphtheria), socialeconomical factors (Income, schooling), alcohol factor, overall thinness (Thinness 5 - 9, thinness 10-19)

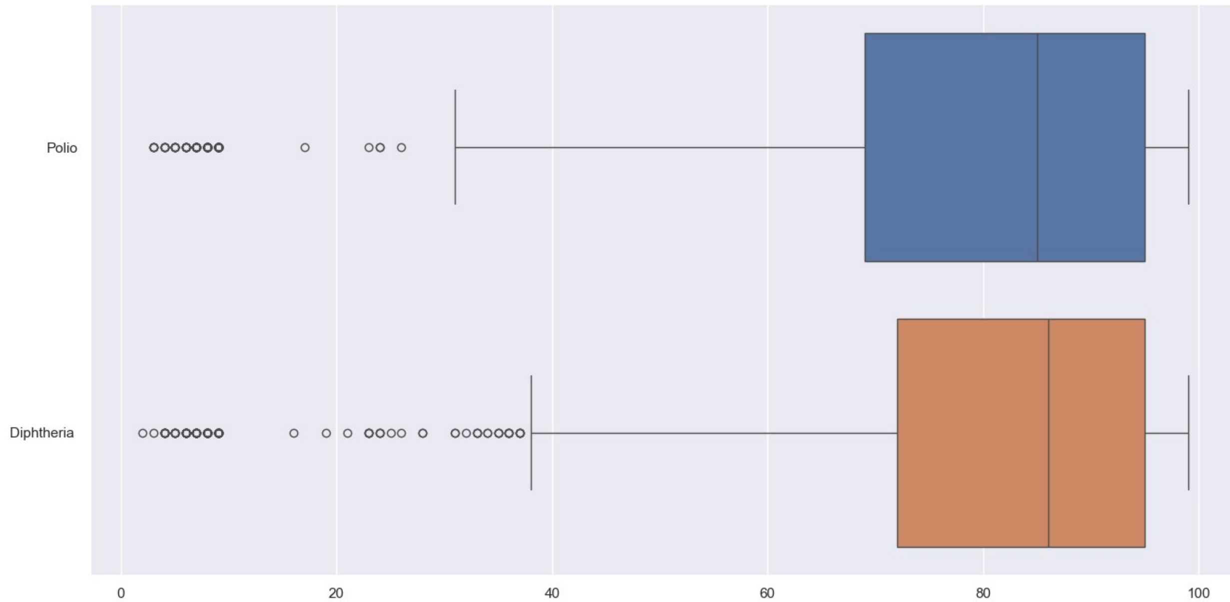
```
sortDF = pd.DataFrame(filtered_data2[["Adult Mortality"]])
sortDF.describe()

f = plt.figure(figsize=(16, 8))
sb.boxplot(data = sortDF, orient = "h")
```

```
<Axes: >
```

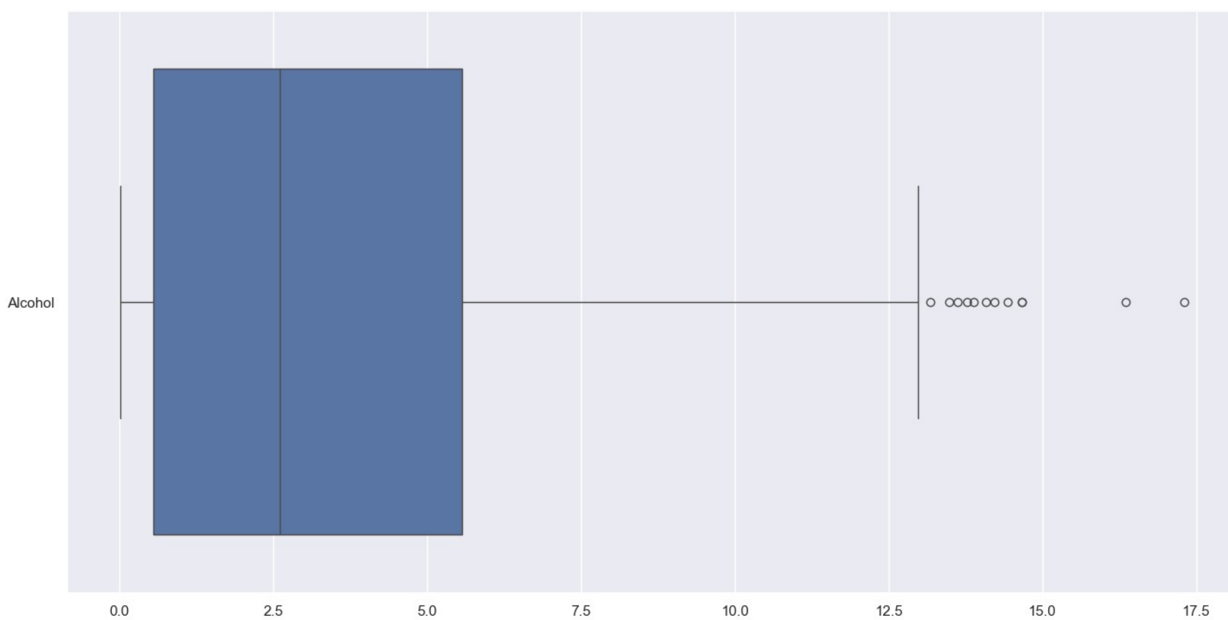



```
sortDF = pd.DataFrame(filtered_data2[["Polio", "Diphtheria " ]])
sortDF.describe()

f = plt.figure(figsize=(16, 8))
sb.boxplot(data = sortDF, orient = "h")
```

```
<Axes: >
```



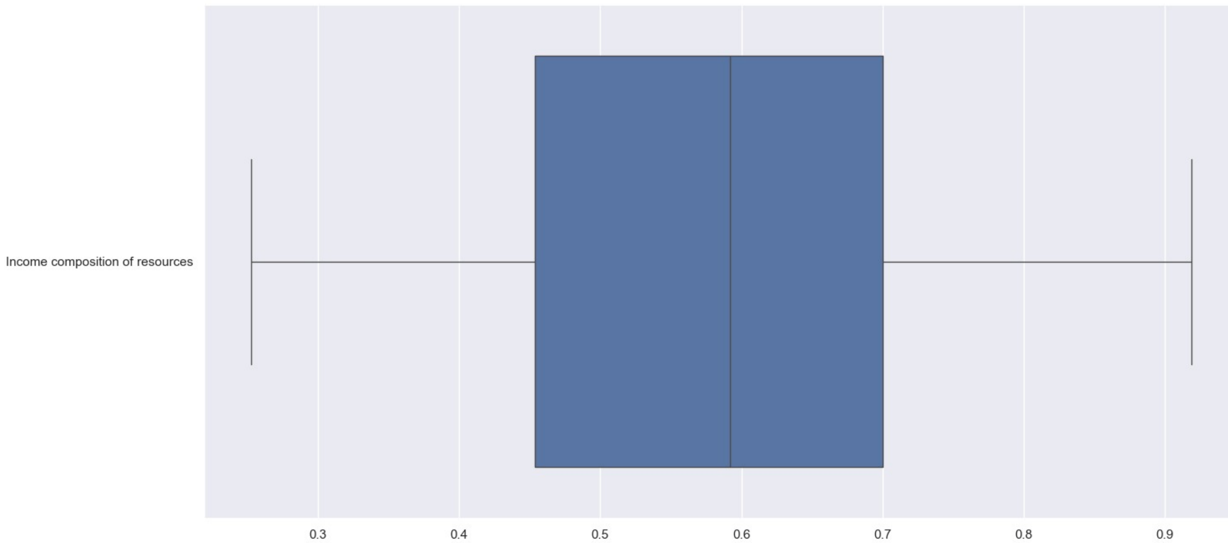

```
sortDF = pd.DataFrame(filtered_data2[["Alcohol" ]])
sortDF.describe()

f = plt.figure(figsize=(16, 8))
sb.boxplot(data = sortDF, orient = "h")

<Axes: >
```




```
sortDF = pd.DataFrame(filtered_data2[[ "Income composition of
resources"]])
sortDF.describe()
```

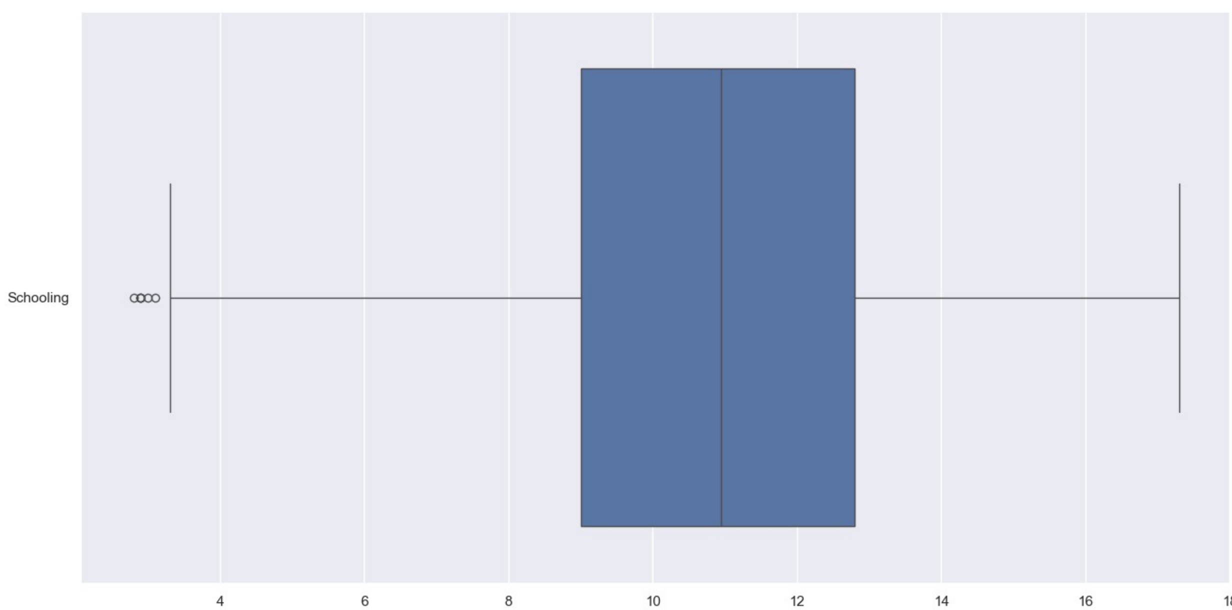
```
f = plt.figure(figsize=(16, 8))
sb.boxplot(data = sortDF, orient = "h")
```

```
<Axes: >
```



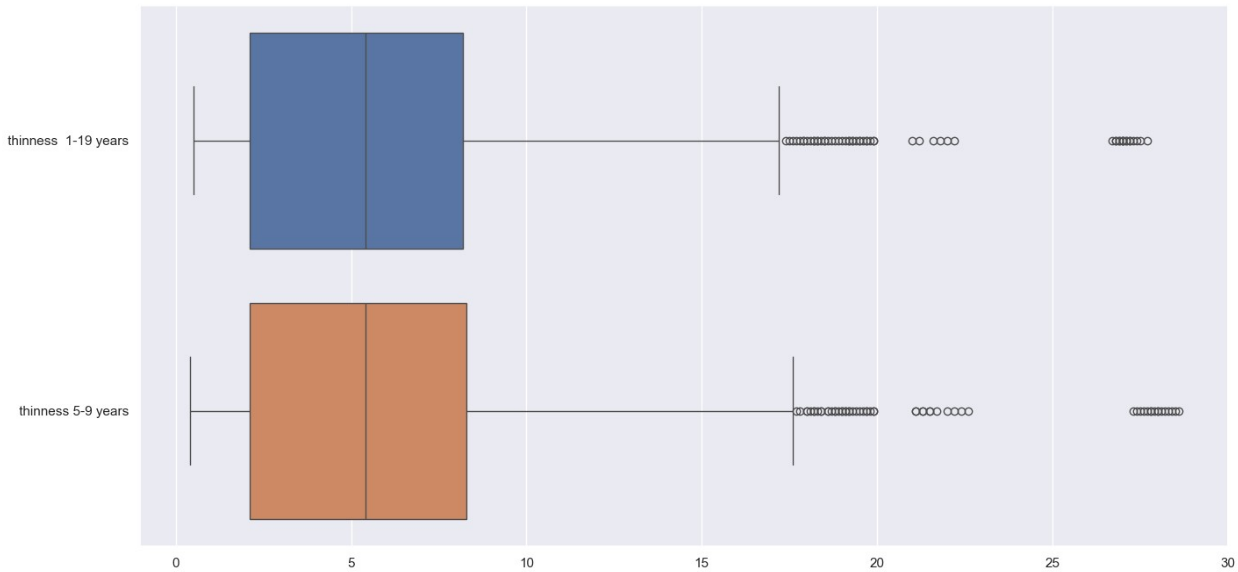

```
sortDF = pd.DataFrame(filtered_data2[[ "Schooling"]])
sortDF.describe()

f = plt.figure(figsize=(16, 8))
sb.boxplot(data = sortDF, orient = "h")
```

```
<Axes: >
```



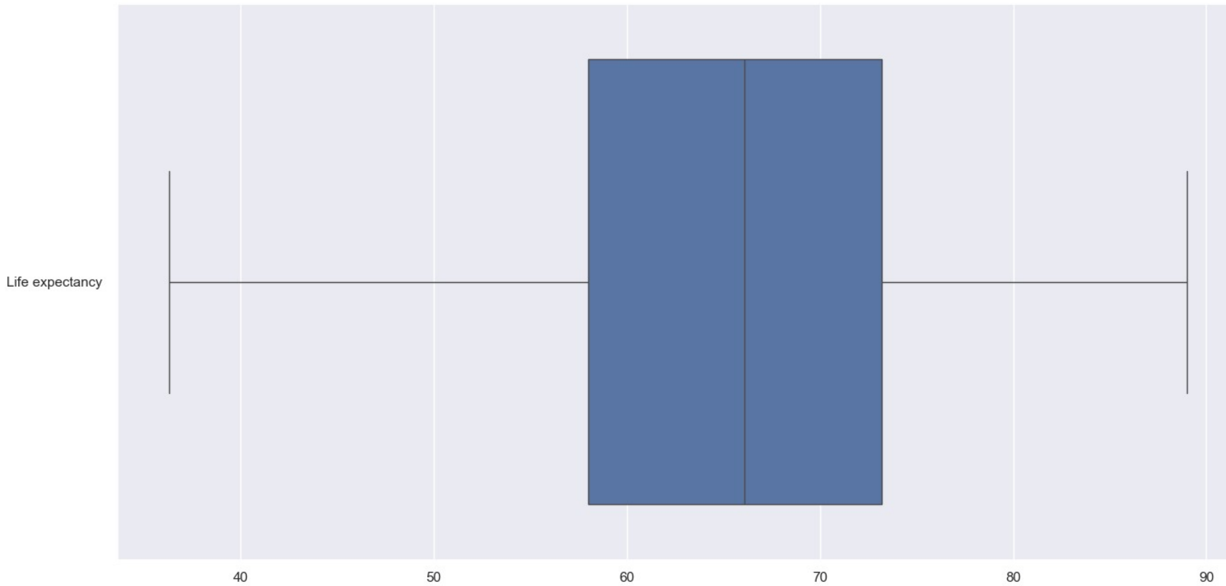
```
sortDF = pd.DataFrame(filtered_data2[[ " thinness  1-19 years", " thinness 5-9 years"]])
sortDF.describe()

f = plt.figure(figsize=(16, 8))
sb.boxplot(data = sortDF, orient = "h")
```

```
<Axes: >
```

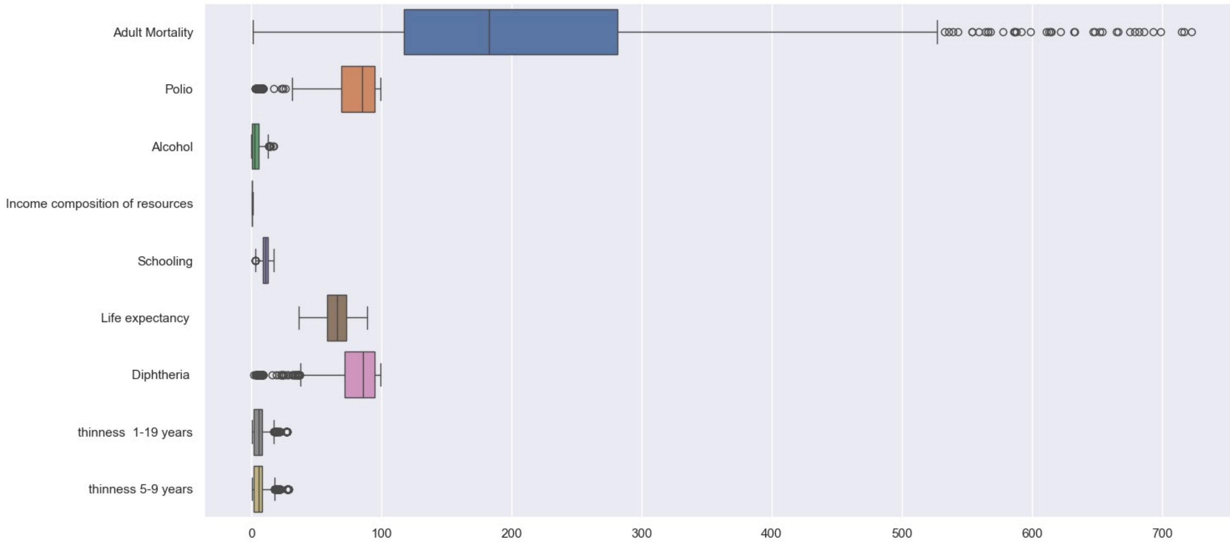


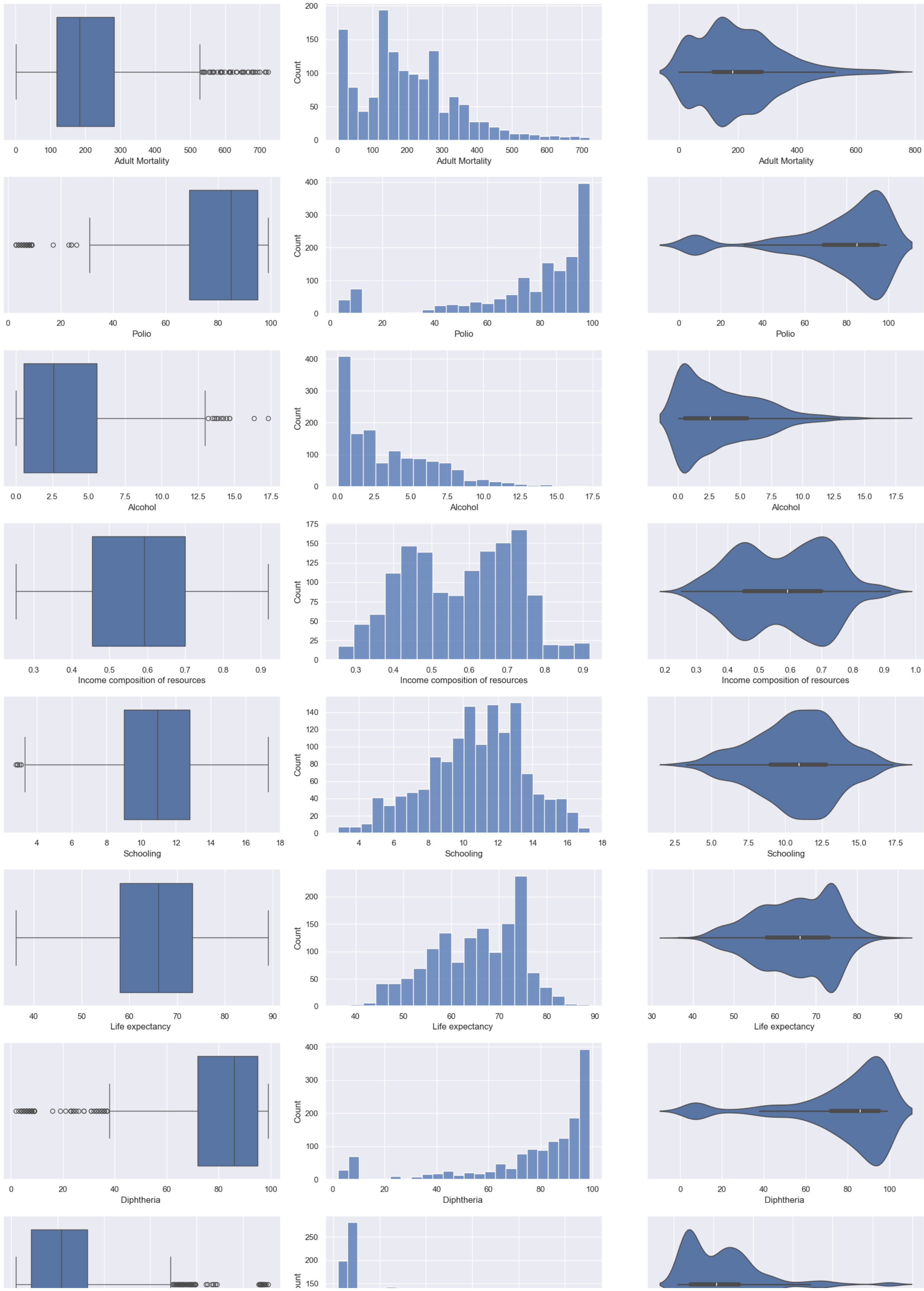

```
sortDF = pd.DataFrame(filtered_data2[[ "Life expectancy "]])
sortDF.describe()

f = plt.figure(figsize=(16, 8))
sb.boxplot(data = sortDF, orient = "h")
```

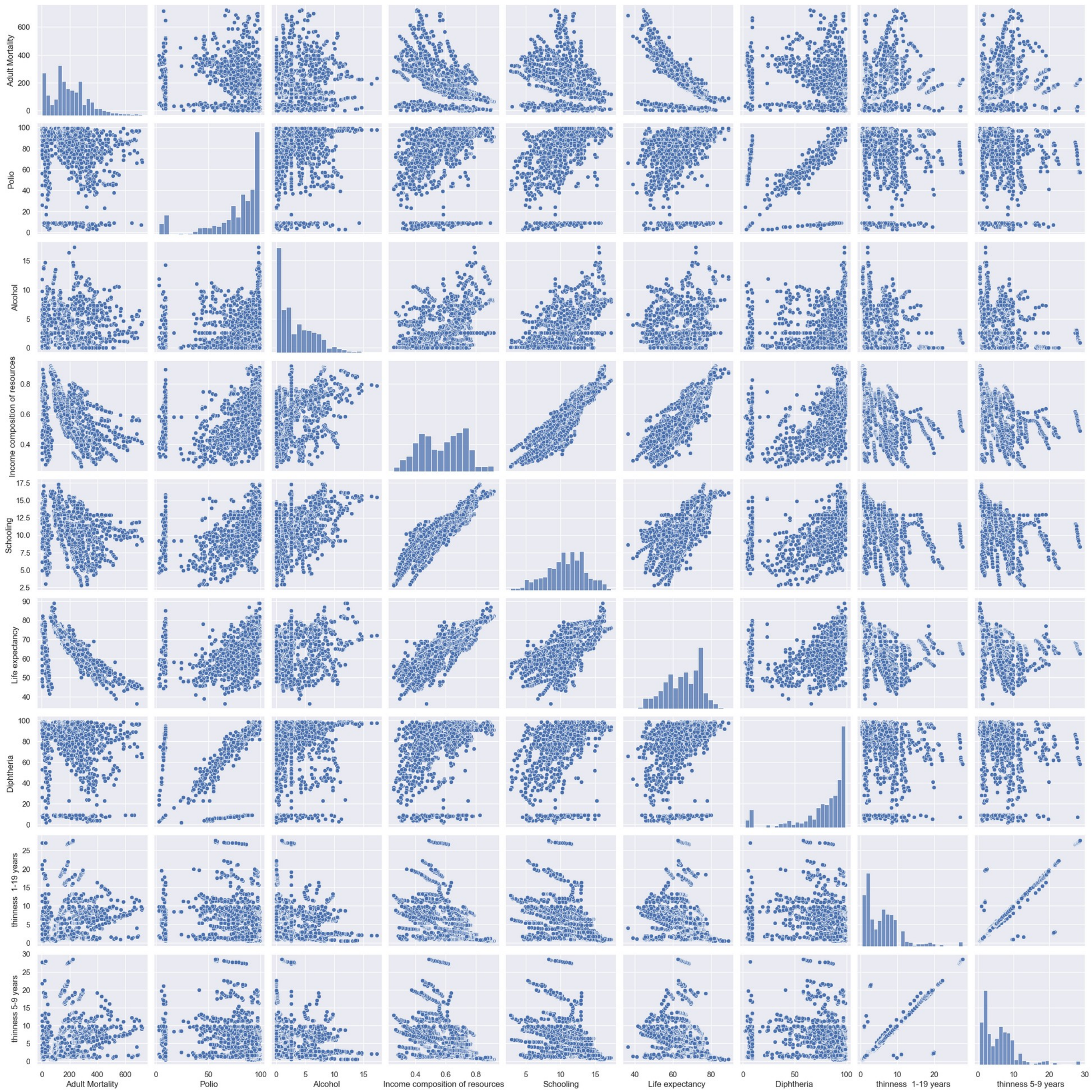
```
<Axes: >
```




```
sortDF = pd.DataFrame(filtered_data2[[
    "Adult Mortality", "Polio", "Alcohol",
    "Income composition of resources", "Schooling",
    "Life expectancy ", "Diphtheria ",
    " thinness  1-19 years", " thinness 5-9 years"
]])

# Boxplot overview
f = plt.figure(figsize=(16, 8))
sb.boxplot(data=sortDF, orient="h")
plt.show()

# Create enough rows to match 9 variables
f, axes = plt.subplots(9, 3, figsize=(18, 30))  # changed from 7 to 9

count = 0
for var in sortDF:
    sb.boxplot(data=sortDF[var], orient="h", ax=axes[count, 0])
    sb.histplot(data=sortDF[var], ax=axes[count, 1])
    sb.violinplot(data=sortDF[var], orient="h", ax=axes[count, 2])
    count += 1

plt.tight_layout()
plt.show()

# Pairplot
sb.pairplot(data=sortDF)
plt.show()
```


Adult Mortality
Polio
Alcohol
Income composition of resources
Schooling
Life expectancy
Diphtheria
thinness 1-19 years
thinness 5-9 years
0
100
200
300
400
500
600
700


Adult Mortality
Count
Adult Mortality
Adult Mortality
Polio
Count
Polio
Polio
Alcohol
Count
Alcohol
Alcohol
Income composition of resources
Count
Income composition of resources
Income composition of resources
Schooling
Count
Schooling
Schooling
Life expectancy
Count
Life expectancy
Life expectancy
Diphtheria
Count
Diphtheria
Diphtheria



Developed

```
developed_data = filtered_data1[filtered_data1['Status'] ==
'Developed']
developed_data.head()

        Country  Year     Status  Life expectancy   Adult Mortality
Alcohol  \
112  Australia  2015  Developed              82.8              59.0
10.24
113  Australia  2014  Developed              82.7               6.0
9.71
```

```
114  Australia  2013  Developed              82.5             61.0
9.87
115  Australia  2012  Developed              82.3             61.0
10.03
116  Australia  2011  Developed              82.0             63.0
10.30

     Hepatitis B  Measles   under-five deaths   Polio  Total
expenditure  \
112         93.0       74                   1   93.0
7.79
113         91.0      340                   1   92.0
9.42
114         91.0      158                   1   91.0
9.36
115         91.0      199                   1   92.0
9.36
116         92.0      190                   1   92.0
9.20

     Diphtheria    HIV/AIDS  Population   thinness  1-19 years  \
112         93.0        0.1  23789338.0                    0.6
113         92.0        0.1   2346694.0                    0.6
114         91.0        0.1  23117353.0                    0.6
115         92.0        0.1  22728254.0                    0.6
116         92.0        0.1    223424.0                    0.6

      thinness 5-9 years  Income composition of resources  Schooling
112                  0.6                            0.937       20.4
113                  0.6                            0.936       20.4
114                  0.6                            0.933       20.3
115                  0.6                            0.930       20.1
116                  0.6                            0.927       19.8
```

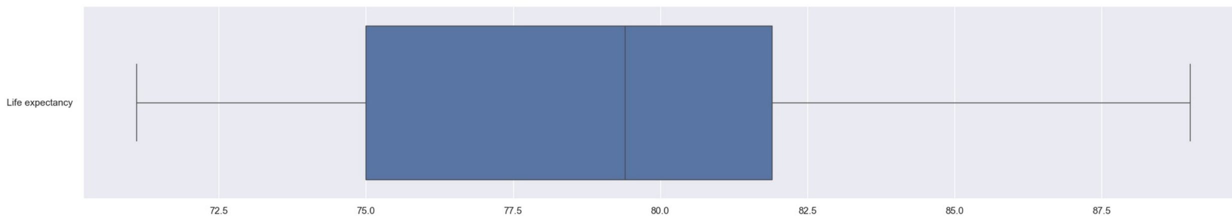
```
lifeex_dlpd = pd.DataFrame(developed_data['Life expectancy '])
lifeex_dlpd.describe()
```

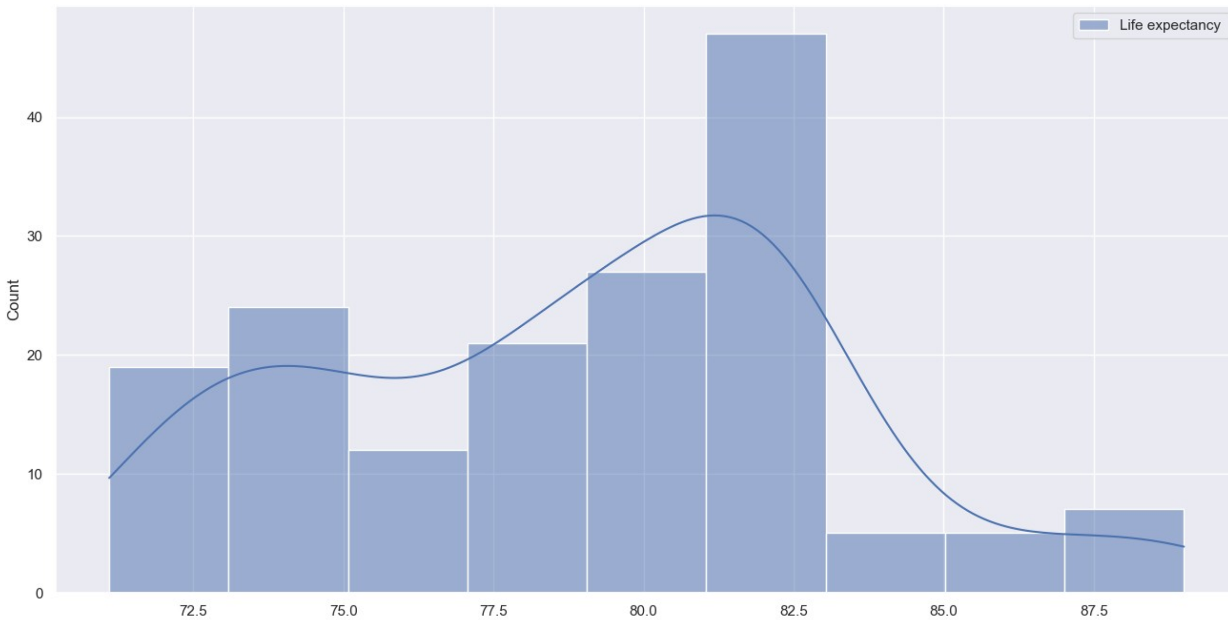
```
       Life expectancy
count       167.000000
mean         78.942515
std           4.300888
min          71.100000
25%          75.000000
50%          79.400000
75%          81.900000
max          89.000000
```

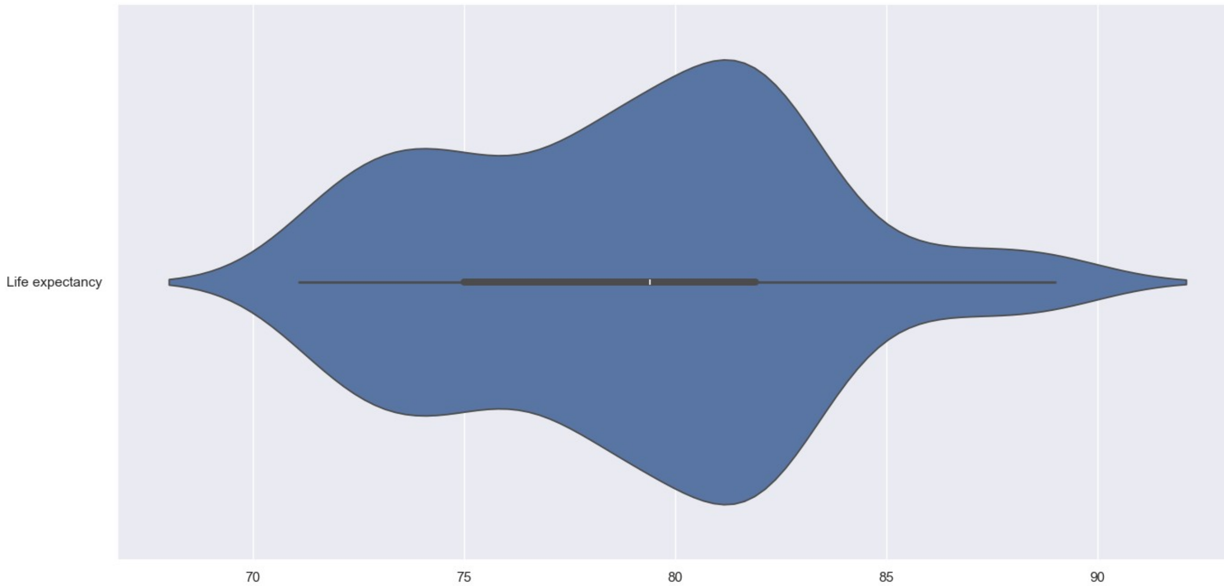
```
f = plt.figure(figsize=(24, 4))
sb.boxplot(data = lifeex_dlpd, orient = "h")
```

```
f = plt.figure(figsize=(16, 8))
sb.histplot(data = lifeex_dlpd, kde = True)

f = plt.figure(figsize=(16, 8))
sb.violinplot(data = lifeex_dlpd, orient = "h")
```

```
<Axes: >
```








```
filtered_data3 = developed_data.drop(columns=["Country", "Year",
"Status", " HIV/AIDS"])
filtered_data3.corr()

                                 Life expectancy  Adult Mortality
Alcohol  \
Life expectancy                         1.000000        -0.574186 -
0.202337
Adult Mortality                        -0.574186         1.000000
0.092018
Alcohol                                -0.202337         0.092018
1.000000
Hepatitis B                             0.001752         0.211795 -
0.144628
Measles                                 0.043164        -0.072637 -
0.144816
under-five deaths                       0.044098         0.122753 -
0.196577
Polio                                  -0.019644         0.065975
0.005839
Total expenditure                       0.021512        -0.168310
0.061049
Diphtheria                             -0.008045        -0.005057 -
0.074418
Population                              0.138946        -0.087803
0.060950
 thinness  1-19 years                  -0.691012         0.657778 -
0.045443
 thinness 5-9 years                    -0.702902         0.674164 -
0.032247
Income composition of resources         0.792909        -0.601816 -
```

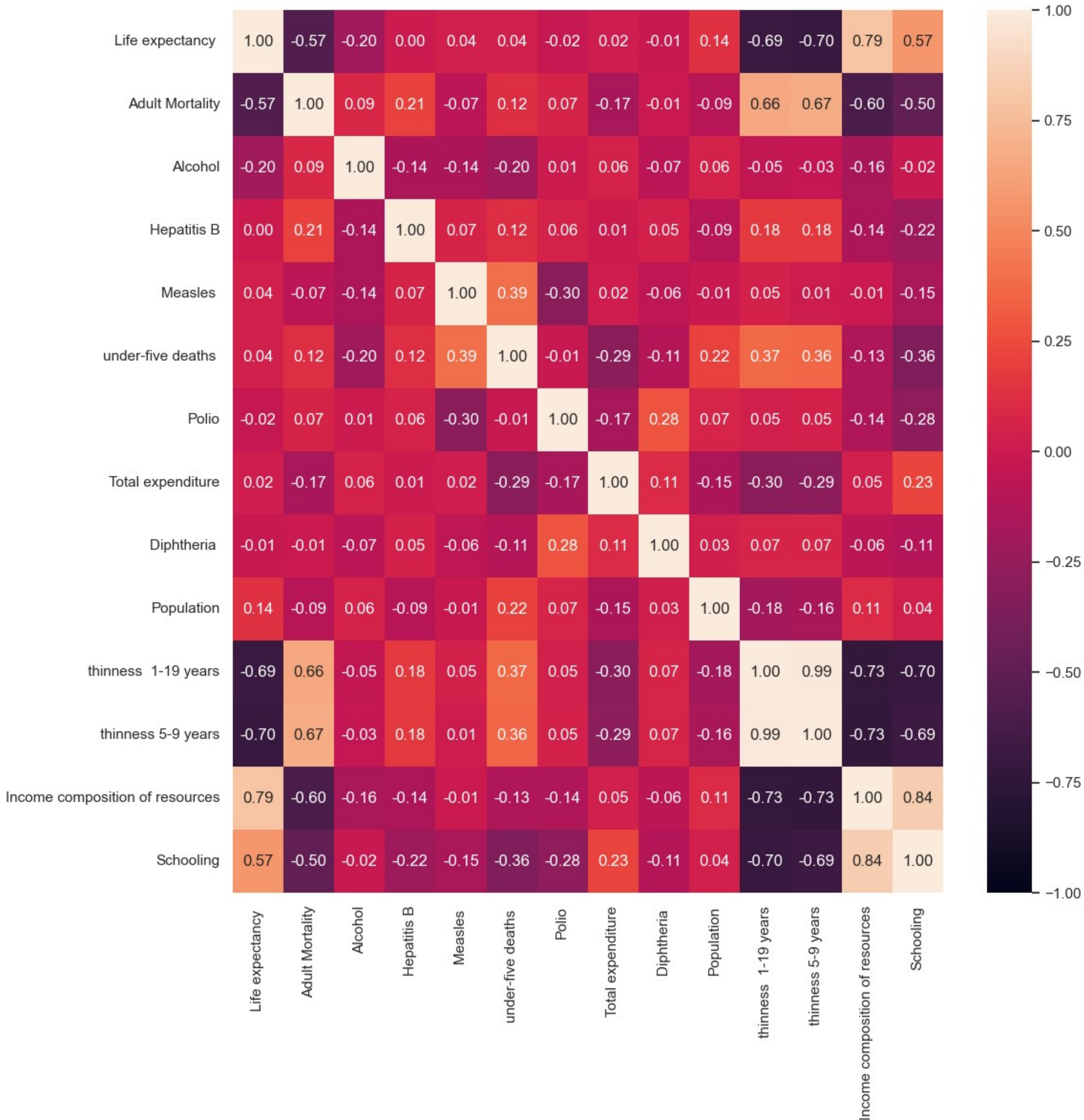
```
0.161276
Schooling                                0.567395        -0.497049 -
0.015507

                                 Hepatitis B  Measles   under-five
deaths   \
Life expectancy                     0.001752  0.043164
0.044098
Adult Mortality                     0.211795 -0.072637
0.122753
Alcohol                            -0.144628 -0.144816            -
0.196577
Hepatitis B                         1.000000  0.066086
0.118331
Measles                             0.066086  1.000000
0.391442
under-five deaths                   0.118331  0.391442
1.000000
Polio                               0.059002 -0.299117            -
0.014177
Total expenditure                   0.005221  0.019906            -
0.292897
Diphtheria                          0.047684 -0.056203            -
0.110609
Population                         -0.091660 -0.014795
0.215786
 thinness  1-19 years               0.178965  0.049030
0.374758
 thinness 5-9 years                 0.179458  0.009348
0.364618
Income composition of resources    -0.143406 -0.006467            -
0.130406
Schooling                          -0.218267 -0.149963            -
0.358683

                                    Polio  Total expenditure
Diphtheria   \
Life expectancy                 -0.019644           0.021512    -
0.008045
Adult Mortality                  0.065975          -0.168310    -
0.005057
Alcohol                          0.005839           0.061049    -
0.074418
Hepatitis B                      0.059002           0.005221
0.047684
Measles                         -0.299117           0.019906    -
0.056203
under-five deaths               -0.014177          -0.292897    -
0.110609
```

```
Polio                                1.000000          -0.167160
0.281832
Total expenditure                   -0.167160           1.000000
0.106287
Diphtheria                           0.281832           0.106287
1.000000
Population                           0.073160          -0.145116
0.033277
 thinness  1-19 years                0.045085          -0.297718
0.073612
 thinness 5-9 years                  0.049910          -0.285963
0.071532
Income composition of resources -0.137111           0.046440    -
0.062821
Schooling                           -0.275446           0.226042    -
0.111541

                                 Population   thinness  1-19 years  \
Life expectancy                    0.138946              -0.691012
Adult Mortality                   -0.087803               0.657778
Alcohol                            0.060950              -0.045443
Hepatitis B                       -0.091660               0.178965
Measles                           -0.014795               0.049030
under-five deaths                  0.215786               0.374758
Polio                              0.073160               0.045085
Total expenditure                 -0.145116              -0.297718
Diphtheria                         0.033277               0.073612
Population                         1.000000              -0.183135
 thinness  1-19 years             -0.183135               1.000000
 thinness 5-9 years               -0.157496               0.992003
Income composition of resources    0.105611              -0.726543
Schooling                          0.040085              -0.703979

                                  thinness 5-9 years  \
Life expectancy                           -0.702902
Adult Mortality                            0.674164
Alcohol                                   -0.032247
Hepatitis B                                0.179458
Measles                                    0.009348
under-five deaths                          0.364618
Polio                                      0.049910
Total expenditure                         -0.285963
Diphtheria                                 0.071532
Population                                -0.157496
 thinness  1-19 years                      0.992003
 thinness 5-9 years                        1.000000
Income composition of resources           -0.733457
Schooling                                 -0.686860

                                 Income composition of resources
```

```
Schooling
Life expectancy                                              0.792909
0.567395
Adult Mortality                                             -0.601816  -
0.497049
Alcohol                                                     -0.161276  -
0.015507
Hepatitis B                                                 -0.143406  -
0.218267
Measles                                                     -0.006467  -
0.149963
under-five deaths                                           -0.130406  -
0.358683
Polio                                                       -0.137111  -
0.275446
Total expenditure                                            0.046440
0.226042
Diphtheria                                                  -0.062821  -
0.111541
Population                                                   0.105611
0.040085
 thinness  1-19 years                                       -0.726543  -
0.703979
 thinness 5-9 years                                         -0.733457  -
0.686860
Income composition of resources                              1.000000
0.836797
Schooling                                                    0.836797
1.000000
```

```
f = plt.figure(figsize=(12, 12))
sb.heatmap(filtered_data3.corr(), vmin = -1, vmax = 1, annot = True,
fmt = ".2f")
```

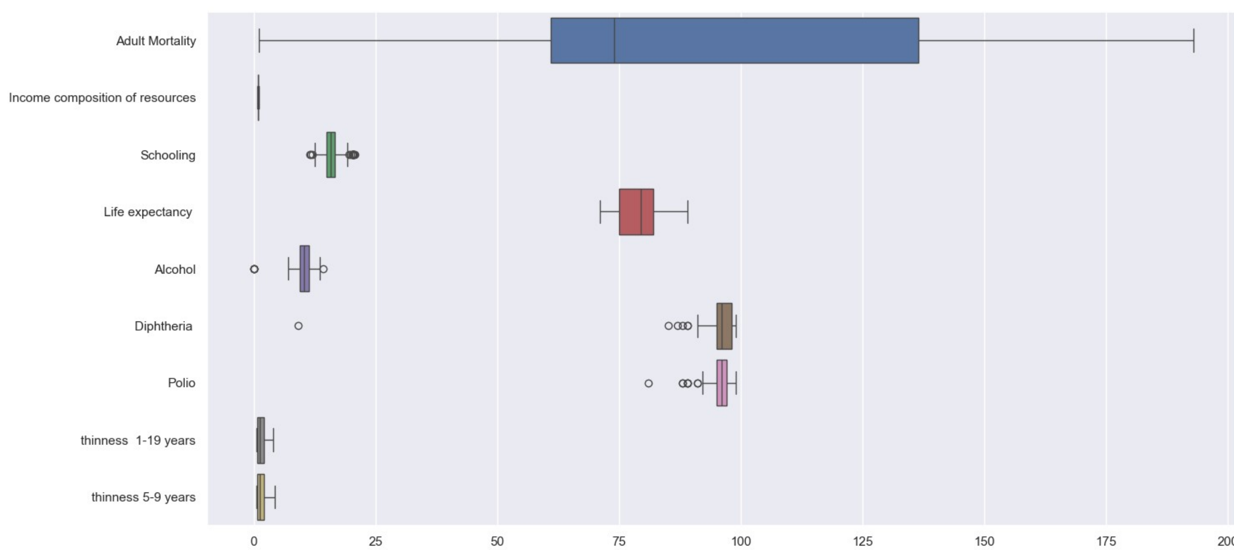
```
<Axes: >
```

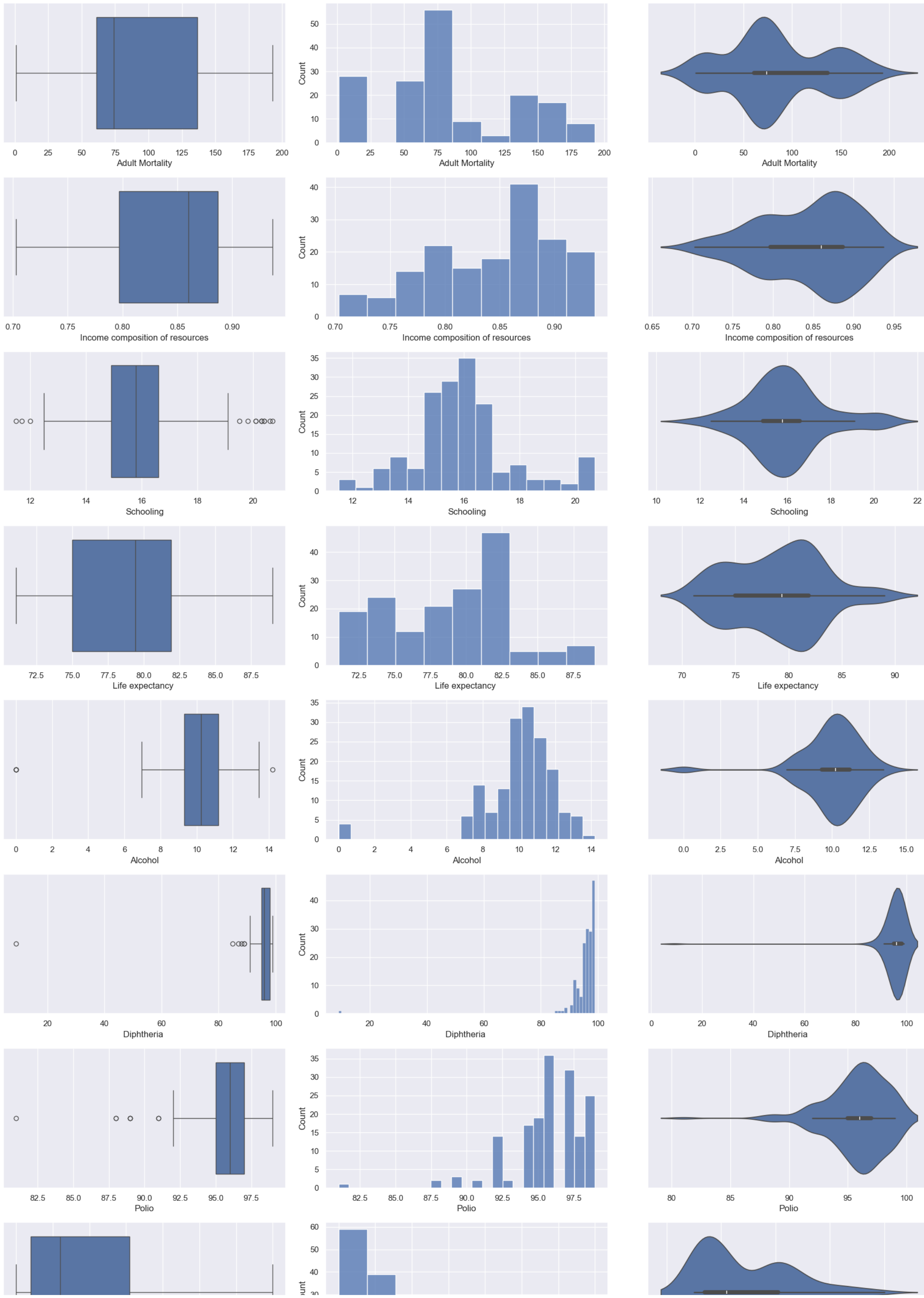


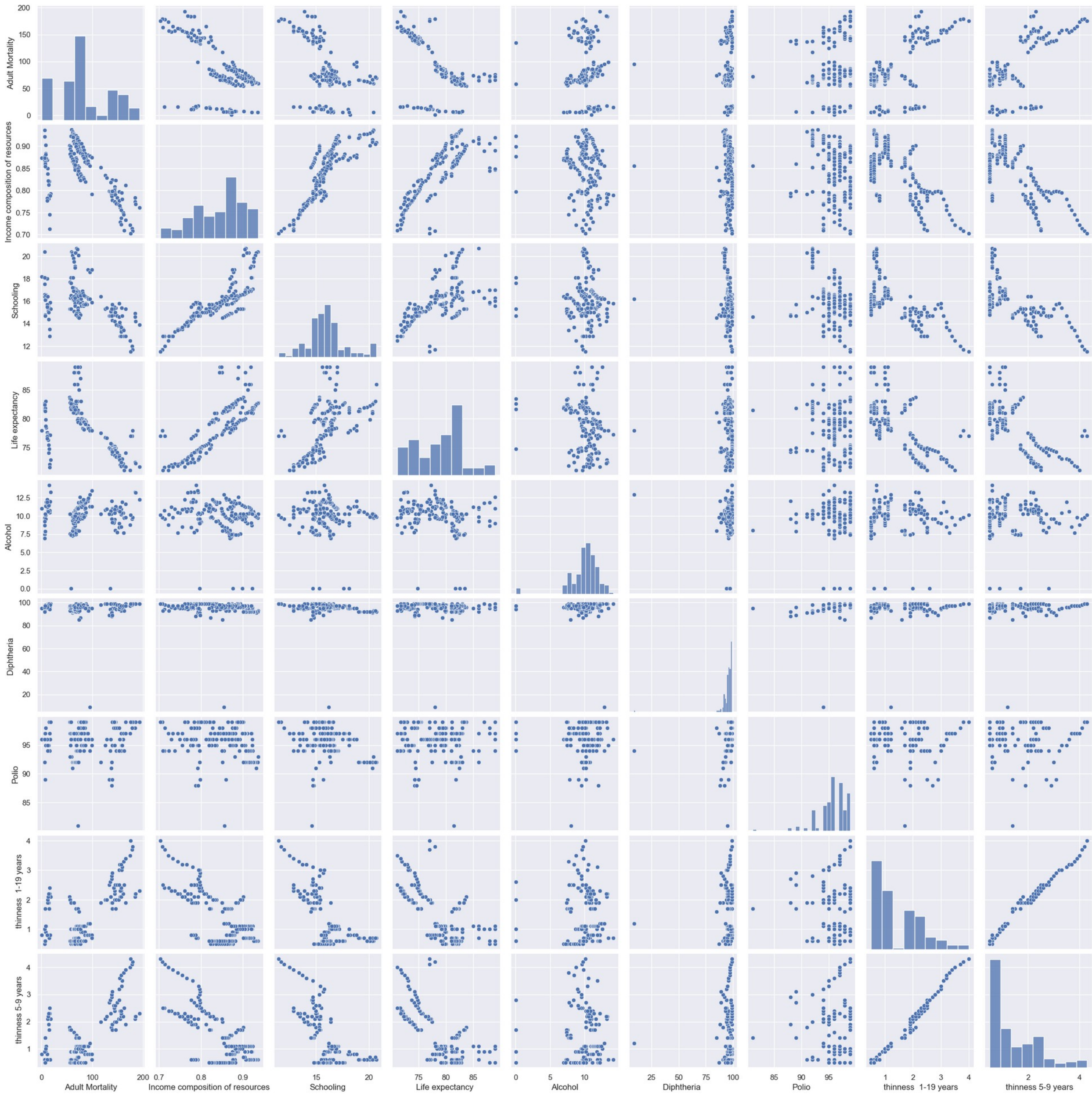
we group health outcomes (adult mortality, HIV/AIDS), immunization coverage (Polio, Diphtheria), socialeconomical factors (Income, schooling), alcohol factor, overall thinness (Thinness 5 - 9, thinness 10-19)

```
import matplotlib.pyplot as plt
import seaborn as sb
import pandas as pd
```

```
numDF = pd.DataFrame(filtered_data3[[
    "Adult Mortality", "Income composition of resources", "Schooling",

    "Life expectancy ", "Alcohol", "Diphtheria ",
    "Polio", " thinness  1-19 years", " thinness 5-9 years"
]])

# Summary stats
numDF.describe()

# Overall boxplot
f = plt.figure(figsize=(16, 8))
sb.boxplot(data=numDF, orient="h")
plt.show()

# □ Fixed: 9 rows (for 9 variables), 3 plots each
f, axes = plt.subplots(9, 3, figsize=(18, 30))

count = 0
for var in numDF:
    sb.boxplot(data=numDF[var], orient="h", ax=axes[count, 0])
    sb.histplot(data=numDF[var], ax=axes[count, 1])
    sb.violinplot(data=numDF[var], orient="h", ax=axes[count, 2])
    count += 1

plt.tight_layout()
plt.show()

# Pairplot
sb.pairplot(data=numDF)
plt.show()
```




Adult Mortality
Count
Income composition of resources
Schooling
Life expectancy
Alcohol
Diphtheria
Polio



Random Forest Function

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

def evaluate_random_forest_regressor(X_train, X_test, y_train, y_test,
feature_name, max_depth=None, n_estimators=100):

    y_train = y_train.values.ravel()
```

```
    y_test = y_test.values.ravel()


    rf_model = RandomForestRegressor(max_depth=max_depth,
n_estimators=n_estimators, random_state=42)
    rf_model.fit(X_train, y_train)


    plt.figure(figsize=(20, 10))
    plot_tree(rf_model.estimators_[0], filled=True,
feature_names=X_train.columns, rounded=True)
    plt.title(f'Decision Tree from Random Forest ({feature_name})')
    plt.show()


    y_train_pred = rf_model.predict(X_train)
    y_test_pred = rf_model.predict(X_test)


    print(f"Train R² Score ({feature_name}):", r2_score(y_train,
y_train_pred))
    print(f"Test R² Score ({feature_name}):", r2_score(y_test,
y_test_pred))

    print(f"Train MSE ({feature_name}):", mean_squared_error(y_train,
y_train_pred))
    print(f"Test MSE ({feature_name}):", mean_squared_error(y_test,
y_test_pred))

    print(f"Train MAE ({feature_name}):", mean_absolute_error(y_train,
y_train_pred))
    print(f"Test MAE ({feature_name}):", mean_absolute_error(y_test,
y_test_pred))
```

XGBoost Function

```
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
import seaborn as sb
import xgboost as xgb
import numpy as np

def evaluate_xgboost_regressor(X_train, X_test, y_train, y_test,
feature_name, max_depth=3, n_estimators=100, learning_rate=0.1):


    xgboost_model = xgb.XGBRegressor(max_depth=max_depth,
n_estimators=n_estimators, learning_rate=learning_rate)
```

```
    xgboost_model.fit(X_train, y_train)


    plt.figure(figsize=(10, 6))
    xgb.plot_importance(xgboost_model, importance_type='weight',
title='Feature Importance', height=0.8)
    plt.show()


    y_train_pred = xgboost_model.predict(X_train)
    y_test_pred = xgboost_model.predict(X_test)


    print("Train R² Score:", r2_score(y_train, y_train_pred))
    print("Test R² Score:", r2_score(y_test, y_test_pred))

    print("Train MSE:", mean_squared_error(y_train, y_train_pred))
    print("Test MSE:", mean_squared_error(y_test, y_test_pred))

    print("Train MAE:", mean_absolute_error(y_train, y_train_pred))
    print("Test MAE:", mean_absolute_error(y_test, y_test_pred))


    reg_line = LinearRegression()
    y_test_array = y_test.values.flatten()
    reg_line.fit(y_test_array.reshape(-1, 1), y_test_pred)
    slope = reg_line.coef_[0]
    intercept = reg_line.intercept_
    print(f"Regression Line Equation (Test): y = {slope:.4f}x +
{intercept:.4f}")


    fig, axes = plt.subplots(1, 2, figsize=(24, 6))


    sb.scatterplot(x=y_train.values.flatten(), y=y_train_pred,
ax=axes[0])
    axes[0].set_title(f"Train: Actual vs Predicted ({feature_name})")
    axes[0].set_xlabel("Actual Values")
    axes[0].set_ylabel("Predicted Values")


    sb.scatterplot(x=y_test_array, y=y_test_pred, ax=axes[1],
label='Predicted')
    axes[1].plot(y_test_array, reg_line.predict(y_test_array.reshape(-
1, 1)), color='red', label='Regression Line')
    axes[1].set_title(f"Test: Actual vs Predicted ({feature_name})")
    axes[1].set_xlabel("Actual Values")
    axes[1].set_ylabel("Predicted Values")
    axes[1].legend()
```

```
    plt.show()
```

Developed XGBoost Starts from here

```
LE_developed = pd.DataFrame(numDF['Life expectancy '])
Diphtheria_developed = pd.DataFrame(numDF["Diphtheria "])
Diphtheria_developed_train, Diphtheria_developed_test,
LE_developed_train, LE_developed_test = split(Diphtheria_developed,
LE_developed, test_size=0.25, random_state=42)

Adult_Mortality_developed = pd.DataFrame(numDF["Adult Mortality"])
Adult_Mortality_developed_train, Adult_Mortality_developed_test,
LE_developed_train, LE_developed_test =
split(Adult_Mortality_developed, LE_developed, test_size=0.25,
random_state=42)

Schooling_developed = pd.DataFrame(numDF["Schooling"])
Schooling_developed_train, Schooling_developed_test,
LE_developed_train, LE_developed_test = split(Schooling_developed,
LE_developed, test_size=0.25, random_state=42)

ICR_developed = pd.DataFrame(numDF["Income composition of resources"])
ICR_developed_train, ICR_developed_test, LE_developed_train,
LE_developed_test = split(ICR_developed, LE_developed, test_size=0.25,
random_state=42)

Diphtheria_developed = pd.DataFrame(numDF["Diphtheria "])
Diphtheria_developed_train, Diphtheria_developed_test,
LE_developed_train, LE_developed_test = split(Diphtheria_developed,
LE_developed, test_size=0.25, random_state=42)

Alcohol_developed = pd.DataFrame(numDF["Alcohol"])
Alcohol_developed_train, Alcohol_developed_test, LE_developed_train,
LE_developed_test = split(Alcohol_developed, LE_developed,
test_size=0.25, random_state=42)

Polio_developed = pd.DataFrame(numDF["Polio"])
Polio_developed_train, Polio_developed_test, LE_developed_train,
LE_developed_test = split(Polio_developed, LE_developed,
test_size=0.25, random_state=42)


Thinness_1_19_developed = pd.DataFrame(numDF[" thinness  1-19 years"])
Thinness_1_19_developed_train, Thinness_1_19_developed_test,
LE_developed_train, LE_developed_test = split(
    Thinness_1_19_developed, LE_developed, test_size=0.25,
random_state=42)
```

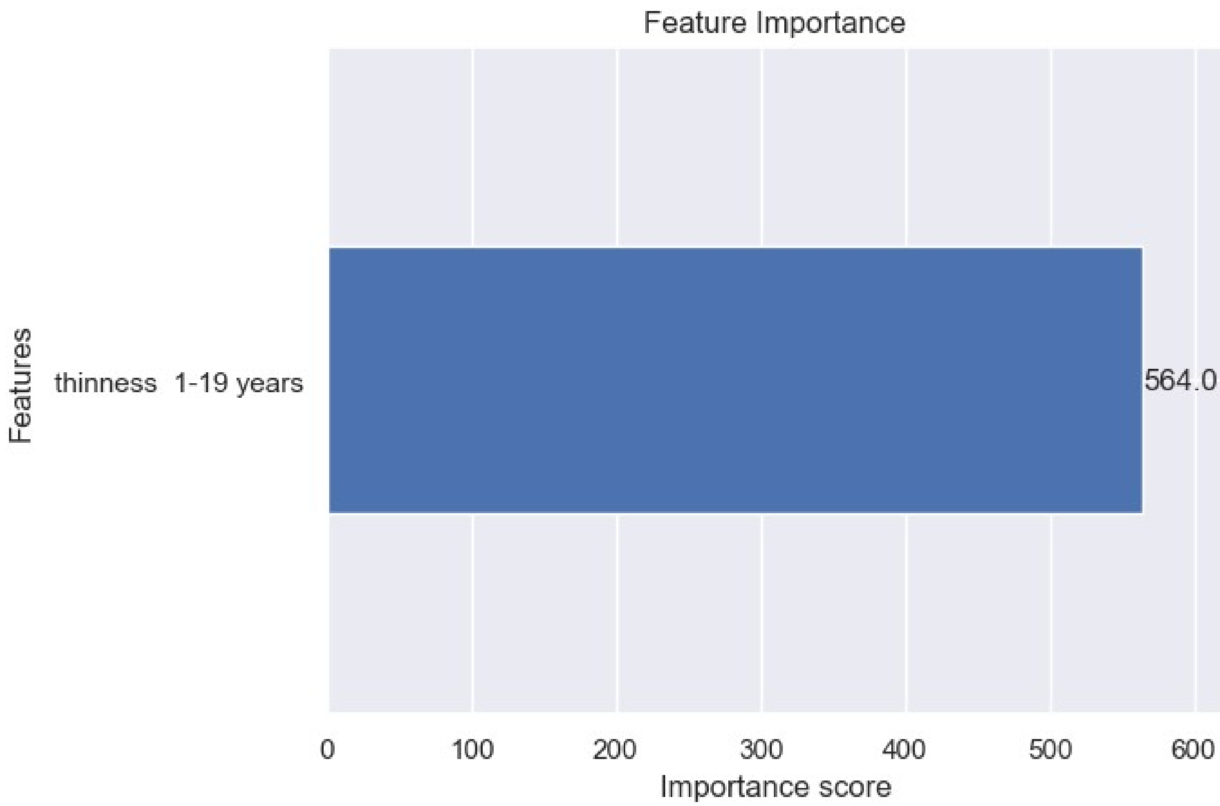
```python
Thinness_5_9_developed = pd.DataFrame(numDF[" thinness 5-9 years"])
Thinness_5_9_developed_train, Thinness_5_9_developed_test,
LE_developed_train, LE_developed_test = split(
    Thinness_5_9_developed, LE_developed, test_size=0.25,
random_state=42)




## Multi_variables for developed

Schooling_ICR_developed = pd.concat([Schooling_developed,
ICR_developed], axis=1)
Schooling_ICR_developed_train, Schooling_ICR_developed_test,
LE_developed_train, LE_developed_test = split(
    Schooling_ICR_developed, LE_developed, test_size=0.25,
random_state=42
)

Diphtheria_Polio_developed = pd.concat([Diphtheria_developed,
Polio_developed], axis=1)
Diphtheria_Polio_developed_train, Diphtheria_Polio_developed_test,
LE_developed_train, LE_developed_test = split(
    Diphtheria_Polio_developed, LE_developed, test_size=0.25,
random_state=42
)


Thinness_Combined_developed = pd.concat([Thinness_1_19_developed,
Thinness_5_9_developed], axis=1)


Thinness_Combined_developed_train, Thinness_Combined_developed_test,
LE_developed_train, LE_developed_test = split(
    Thinness_Combined_developed, LE_developed, test_size=0.25,
random_state=42
)
```

XGBoost for developed

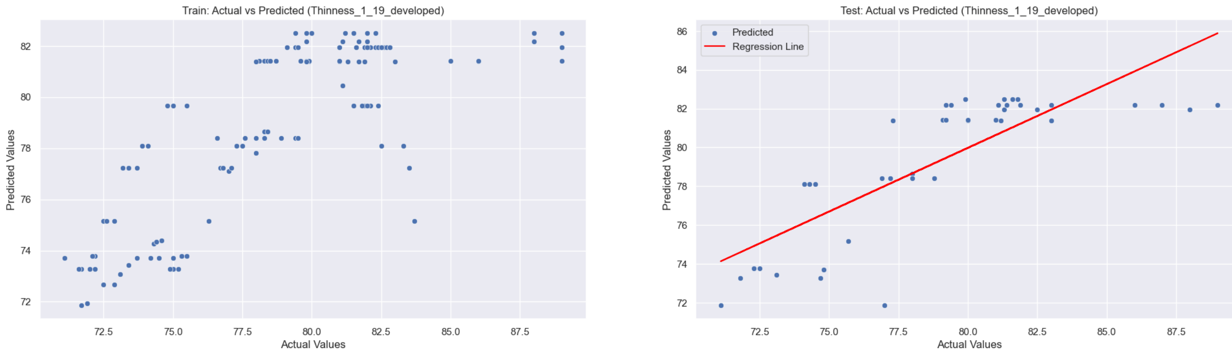
```python
evaluate_xgboost_regressor(
    Thinness_1_19_developed_train, Thinness_1_19_developed_test,
LE_developed_train, LE_developed_test,
    feature_name="Thinness_1_19_developed",
    max_depth=3, n_estimators=100, learning_rate=0.1
)

evaluate_xgboost_regressor(
    Thinness_5_9_developed_train, Thinness_5_9_developed_test,
```

```
LE_developed_train, LE_developed_test,
    feature_name="Thinness_5_9_developed",
    max_depth=3, n_estimators=100, learning_rate=0.1
)
```

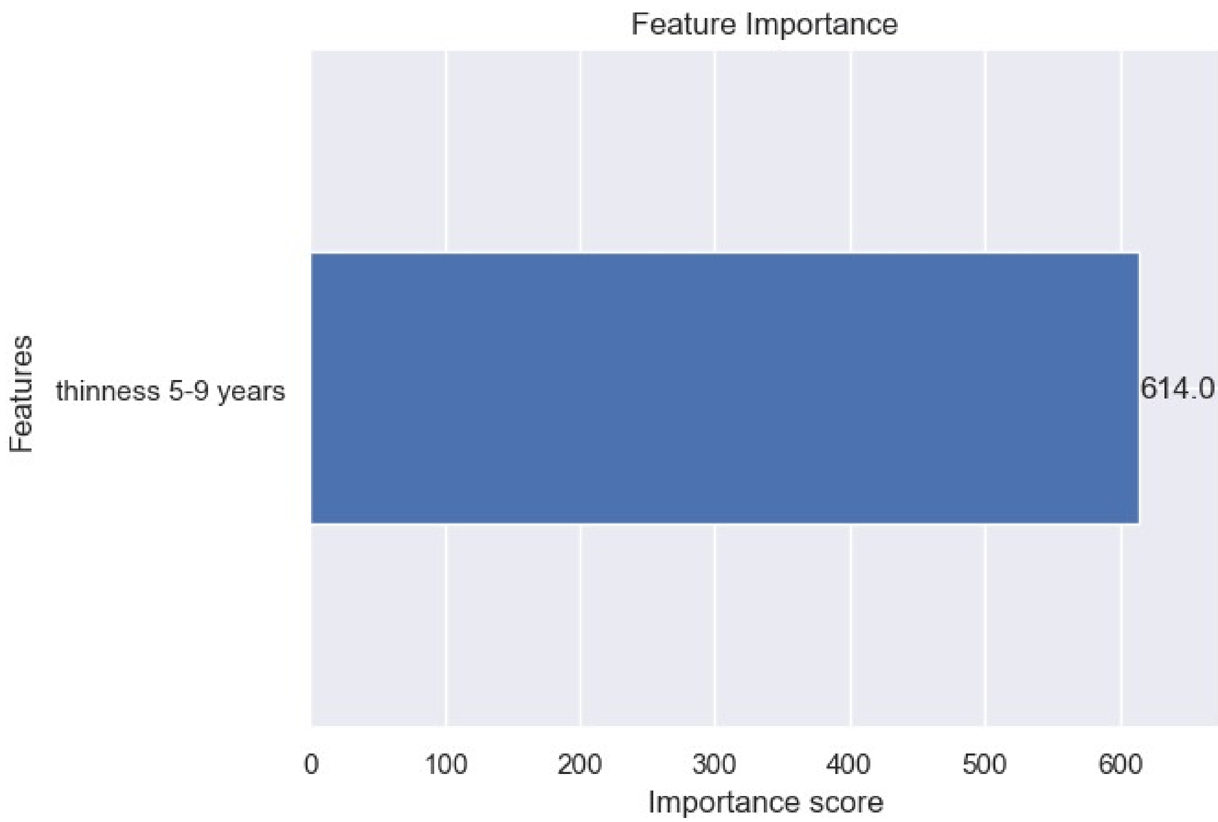
```
<Figure size 1000x600 with 0 Axes>
```




```
Train R² Score: 0.620092547154844
Test R² Score: 0.6502892162529772
Train MSE: 6.97022197154984
Test MSE: 6.456866420331257
Train MAE: 1.8940630126953126
Test MAE: 1.9325550624302459
Regression Line Equation (Test): y = 0.6569x + 27.4244
```



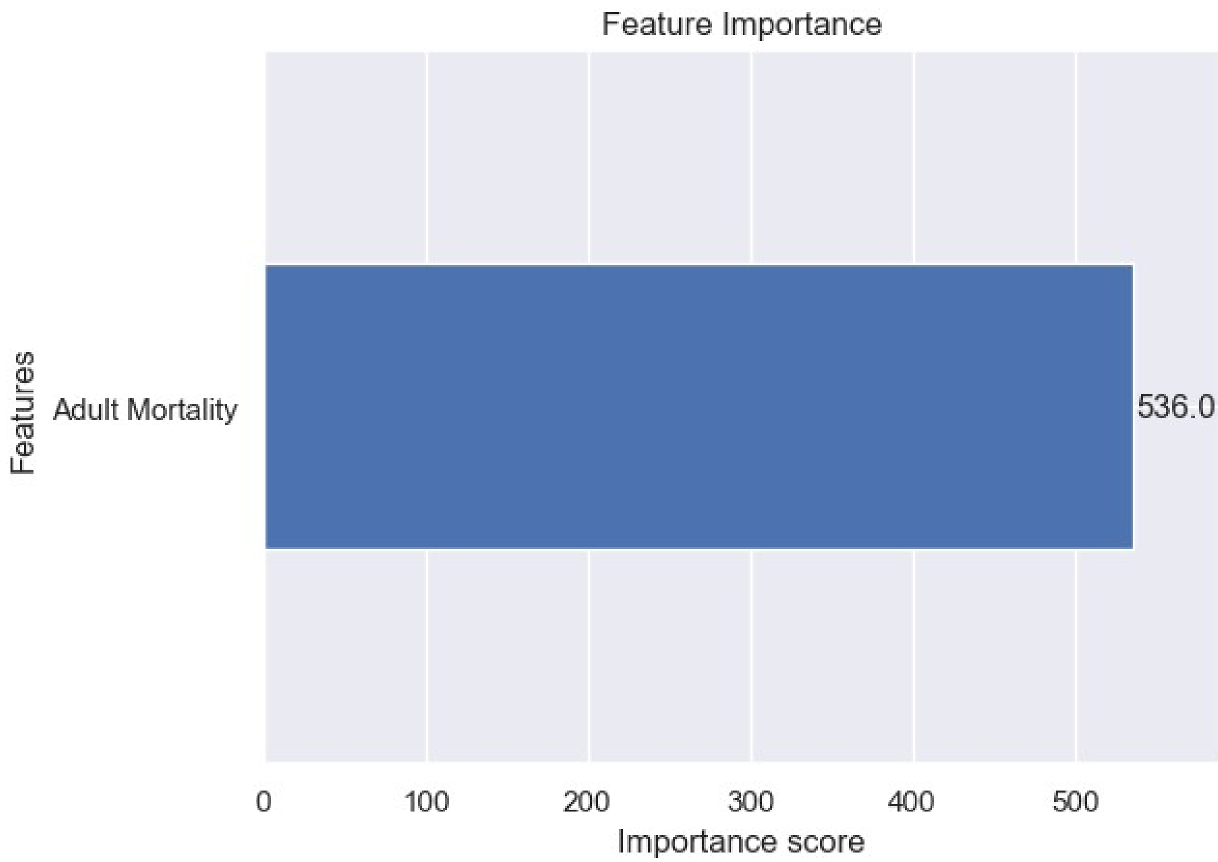

```
<Figure size 1000x600 with 0 Axes>
```



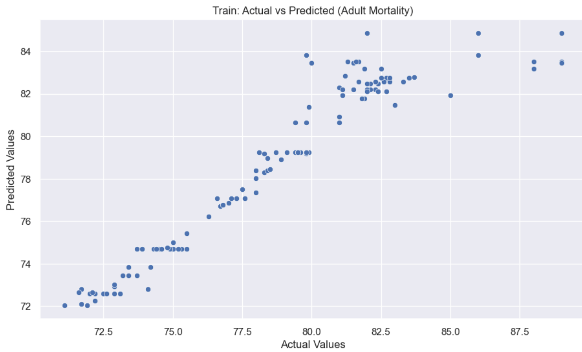

```
Train R² Score: 0.7112757648073522
Test R² Score: 0.5099039209794558
Train MSE: 5.297269092214854
Test MSE: 9.048862838764851
Train MAE: 1.6153812255859374
Test MAE: 2.114008948916481
Regression Line Equation (Test): y = 0.6162x + 30.7531
```

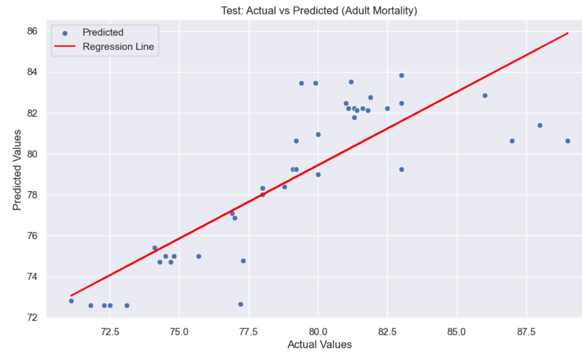

```
# Adult Mortality
evaluate_xgboost_regressor(
    Adult_Mortality_developed_train, Adult_Mortality_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Adult Mortality",
    max_depth=3, n_estimators=100, learning_rate=0.1
)


# Schooling
evaluate_xgboost_regressor(
    Schooling_developed_train, Schooling_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Schooling",
    max_depth=3, n_estimators=100, learning_rate=0.1
)

# Income Composition of Resources (ICR)
evaluate_xgboost_regressor(
    ICR_developed_train, ICR_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="ICR",
    max_depth=3, n_estimators=100, learning_rate=0.1
)

# Diphtheria
evaluate_xgboost_regressor(
    Diphtheria_developed_train, Diphtheria_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Diphtheria",
    max_depth=3, n_estimators=100, learning_rate=0.1
)

# Alcohol
evaluate_xgboost_regressor(
    Alcohol_developed_train, Alcohol_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Alcohol",
    max_depth=3, n_estimators=100, learning_rate=0.1
```

```
)

evaluate_xgboost_regressor(
    Polio_developed_train, Polio_developed_test, LE_developed_train,
LE_developed_test,
    feature_name="Alcohol",
    max_depth=3, n_estimators=100, learning_rate=0.1
)

<Figure size 1000x600 with 0 Axes>
```

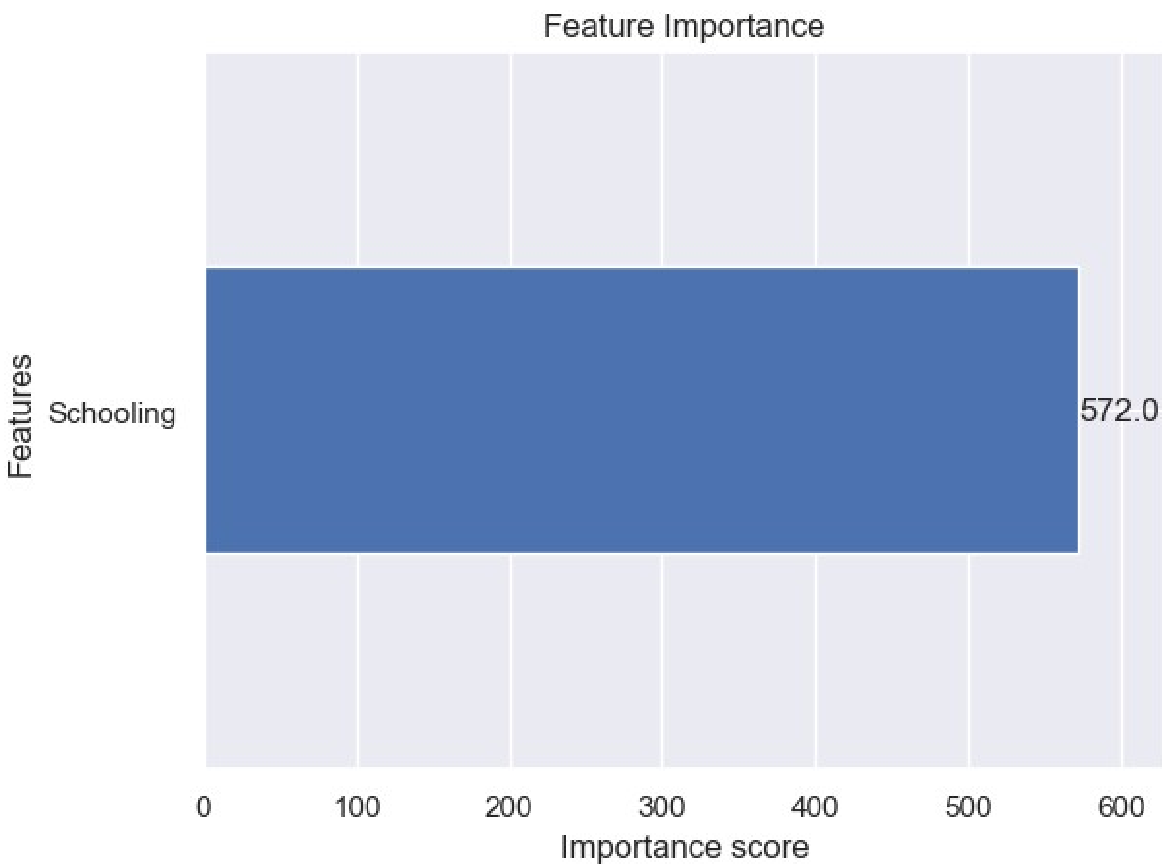



```
Train R² Score: 0.8968320253468012
Test R² Score: 0.6679880419524512
Train MSE: 1.8928391067419201
Test MSE: 6.1300850951637225
Train MAE: 0.8034477050781247
Test MAE: 1.5359083629789807
Regression Line Equation (Test): y = 0.7163x + 22.1300
```

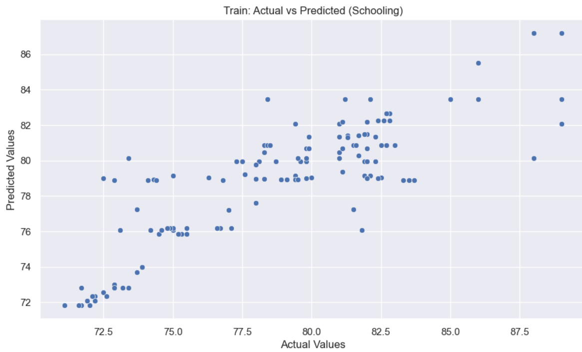


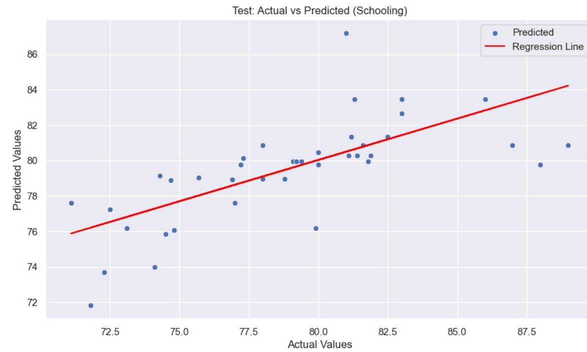



```
<Figure size 1000x600 with 0 Axes>
```

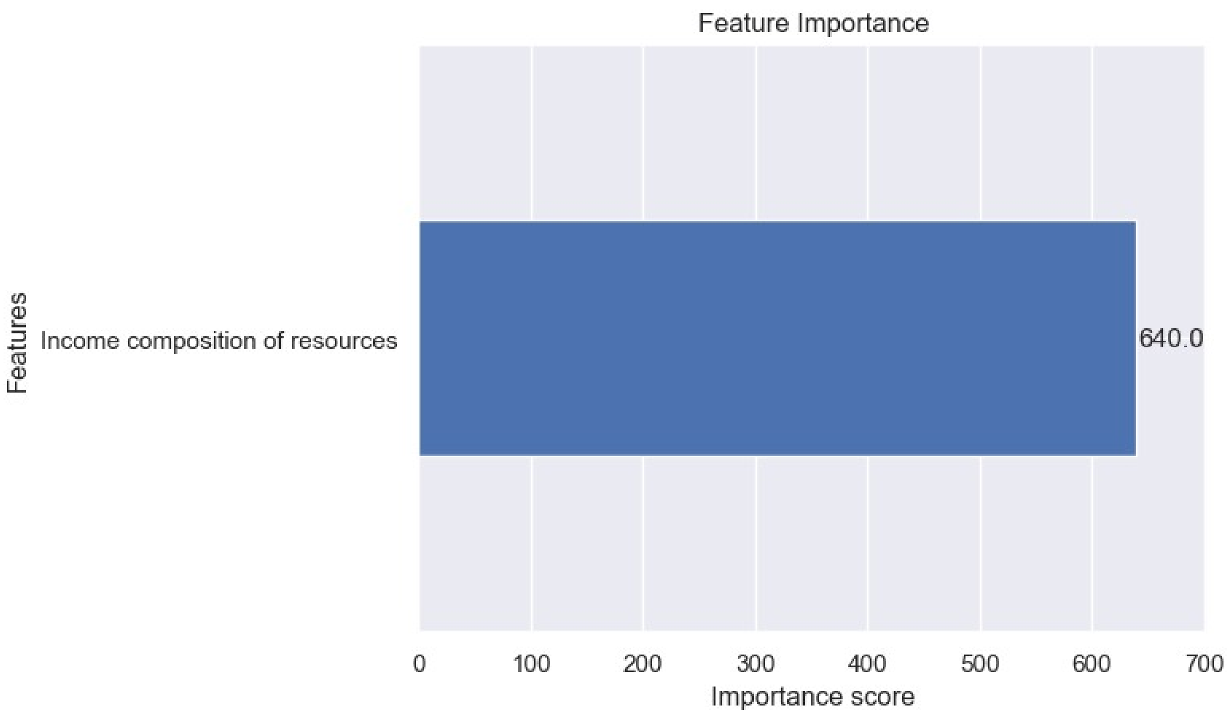



```
Train R² Score: 0.6791519039276566
Test R² Score: 0.46820325624797965
Train MSE: 5.886650635634921
Test MSE: 9.818800839890198
Train MAE: 1.6895447021484375
Test MAE: 2.2497920445033484
Regression Line Equation (Test): y = 0.4661x + 42.7464
```

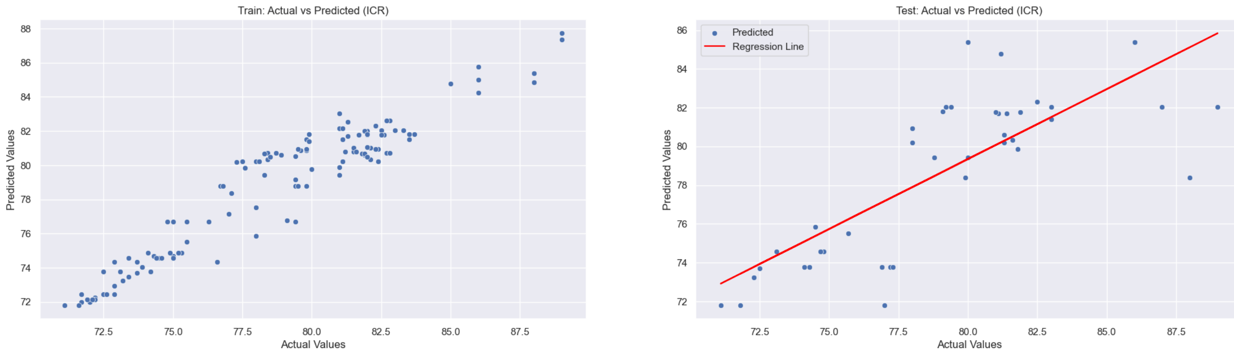




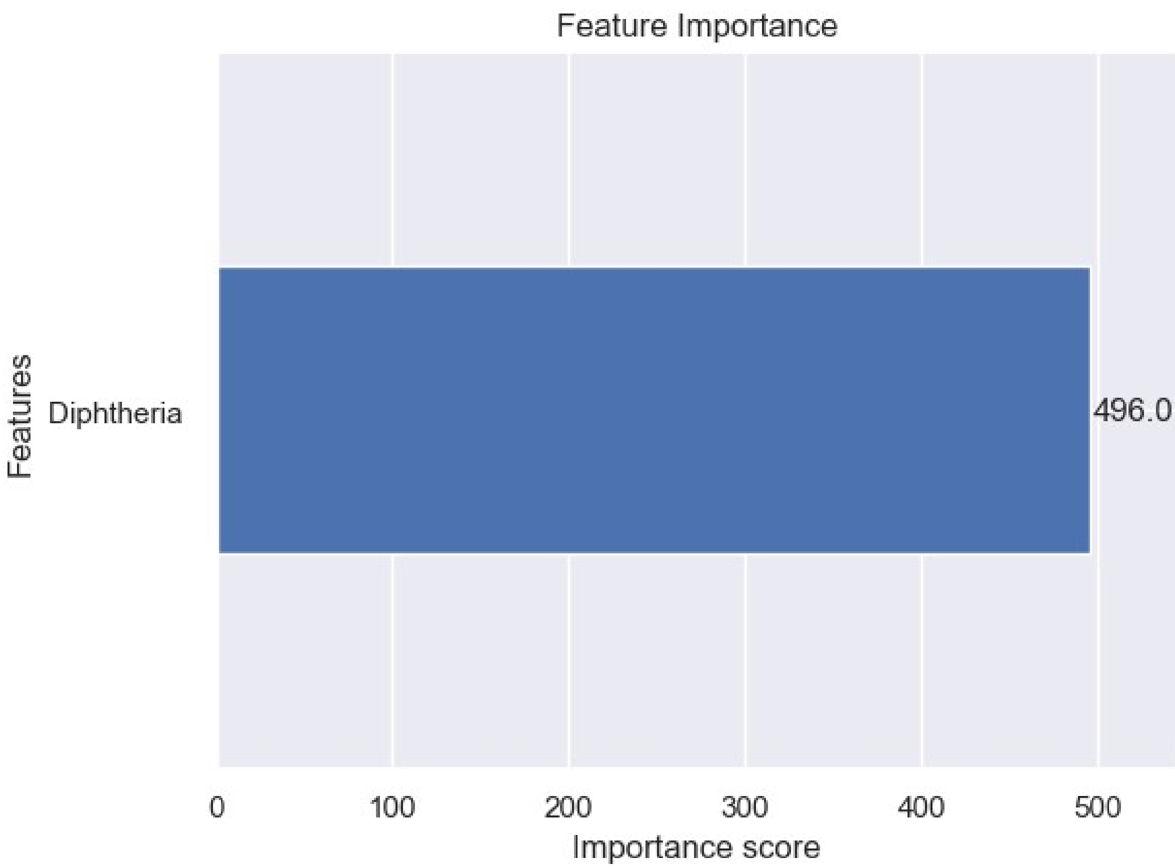

```
<Figure size 1000x600 with 0 Axes>
```



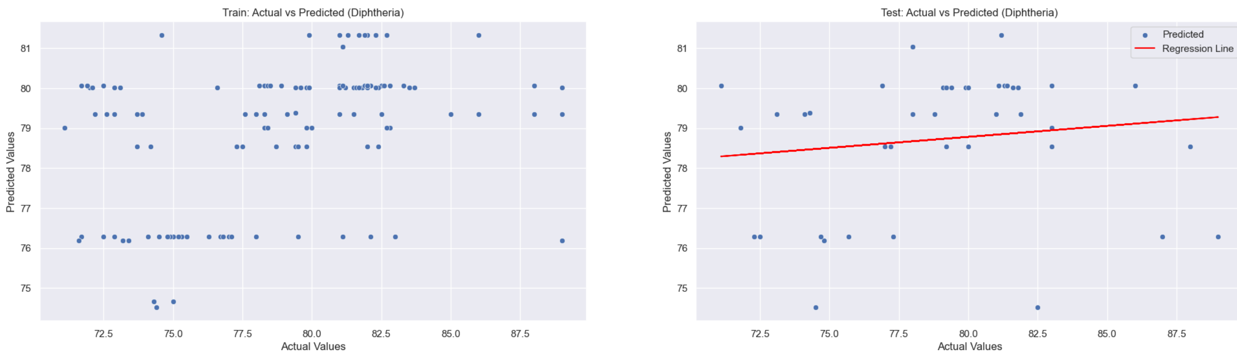

```
Train R² Score: 0.9074980875463817
Test R² Score: 0.565367719962142
Train MSE: 1.6971471808882432
Test MSE: 8.02480994180194
Train MAE: 1.0259440429687499
Test MAE: 1.9866480872744607
Regression Line Equation (Test): y = 0.7223x + 21.5549
```



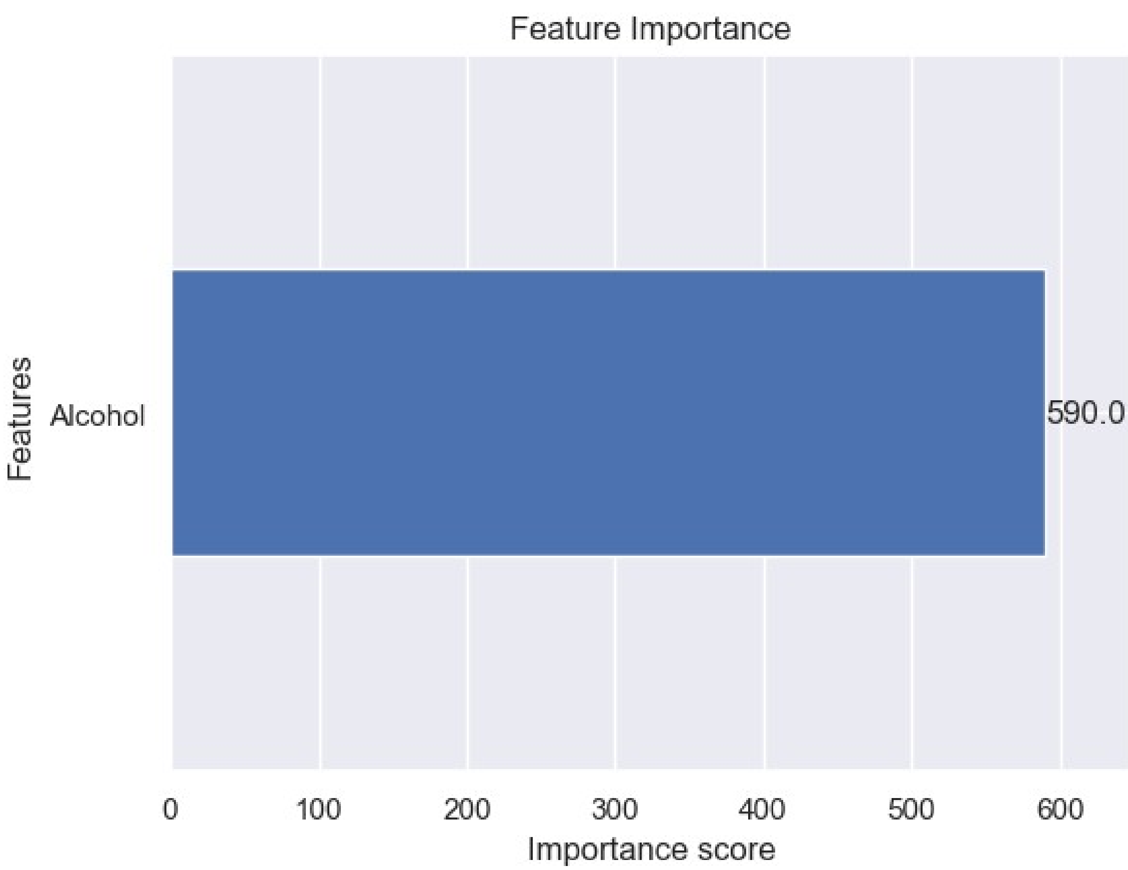

```
<Figure size 1000x600 with 0 Axes>
```



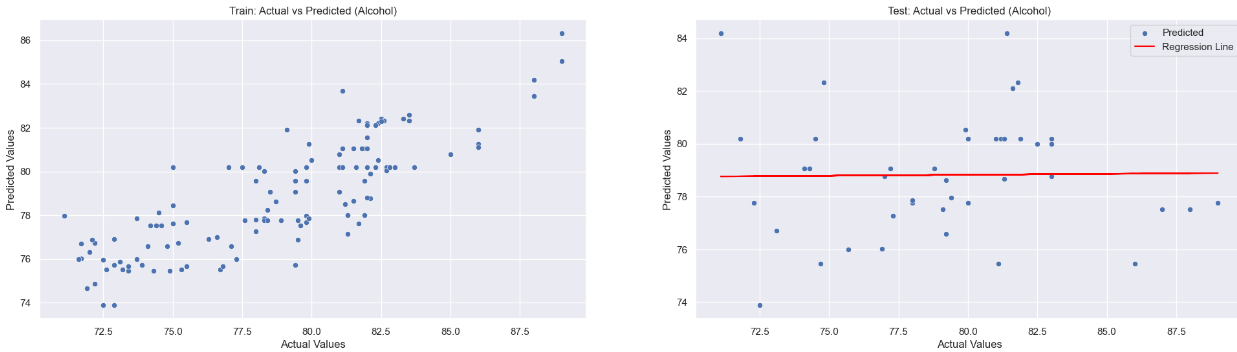

```
Train R² Score: 0.16816975447282623
Test R² Score: -0.05857590664639023
Train MSE: 15.261720744226594
Test MSE: 19.544959842991922
Train MAE: 2.8645980590820317
Test MAE: 3.129350317092169
Regression Line Equation (Test): y = 0.0550x + 74.3868
```



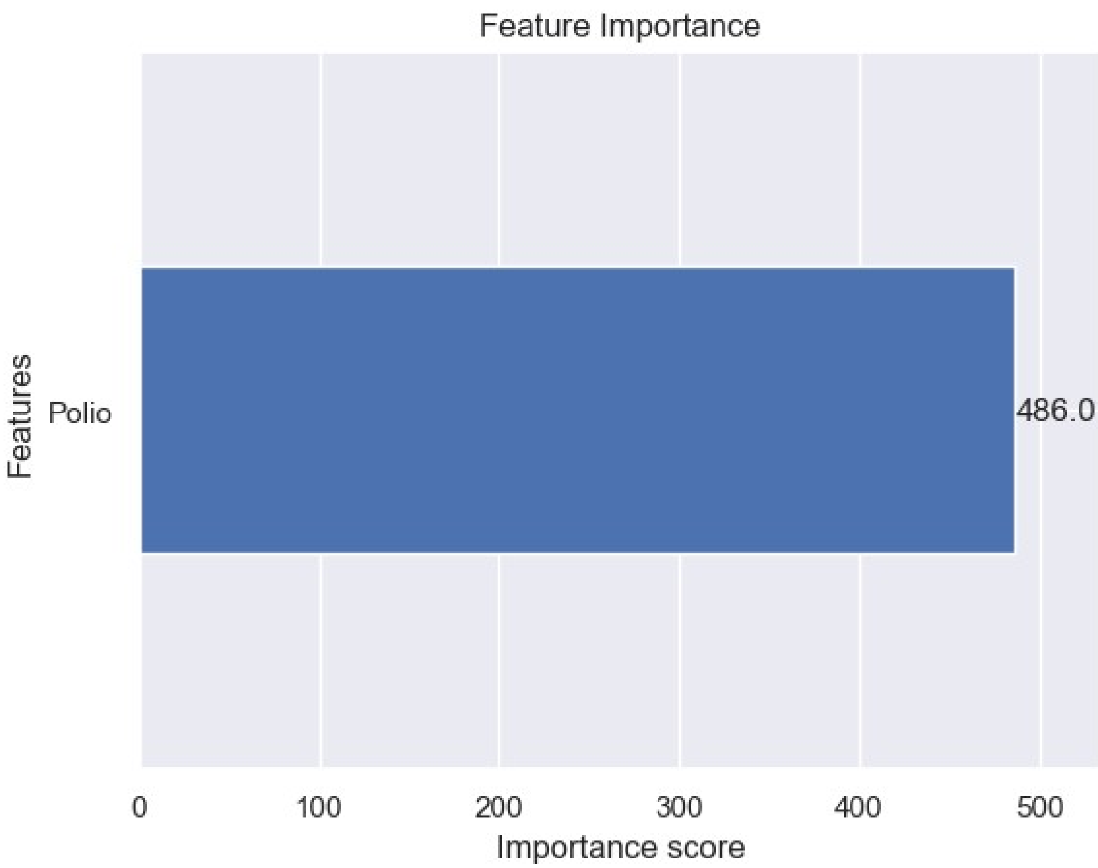

```
&lt;Figure size 1000x600 with 0 Axes&gt;
```



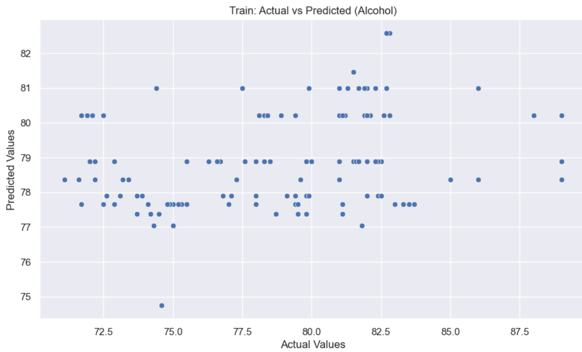

```
Train R² Score: 0.6467717677611333
Test R² Score: -0.2628496970036449
Train MSE: 6.480734102172405
Test MSE: 23.316558085915062
Train MAE: 2.0729410156249997
Test MAE: 3.367533656529018
Regression Line Equation (Test): y = 0.0071x + 78.2599
```

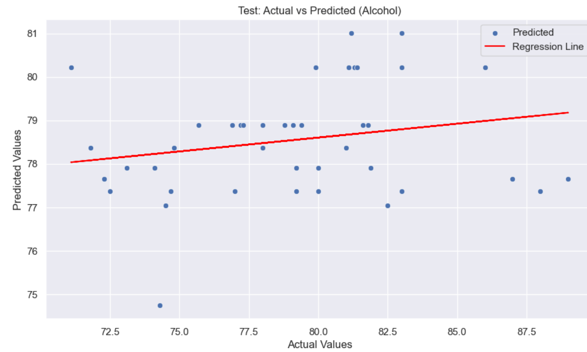



```
<Figure size 1000x600 with 0 Axes>
```



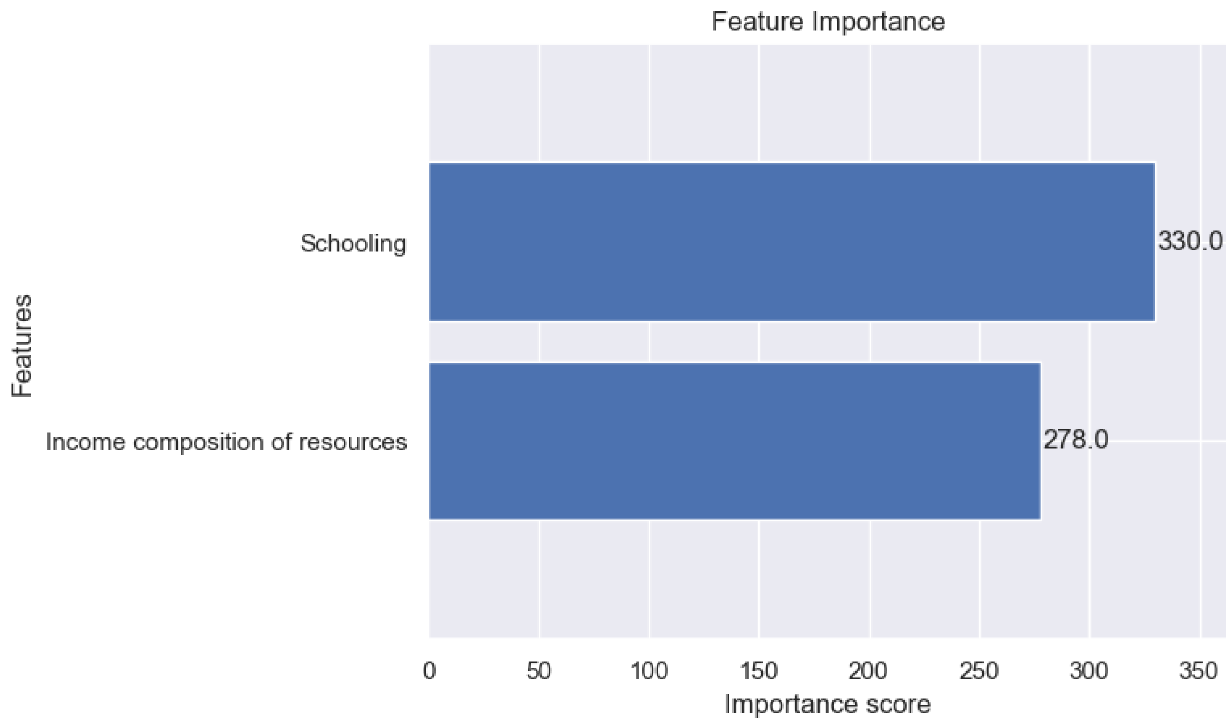

```
Train R² Score: 0.10010062617837179
Test R² Score: 0.02127167623914239
Train MSE: 16.510595779630627
Test MSE: 18.07069825130144
Train MAE: 3.2432973754882815
Test MAE: 3.15413574945359
Regression Line Equation (Test): y = 0.0637x + 73.5056
```



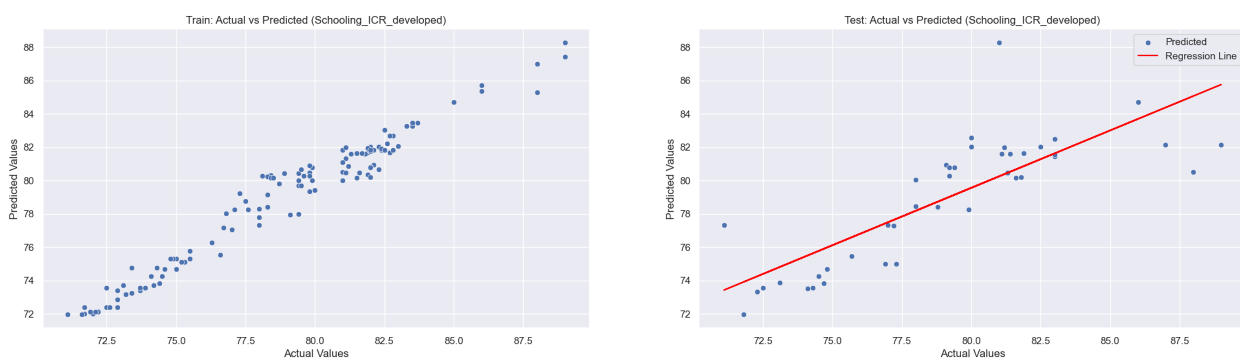


XGBoost for developed mutli-variate

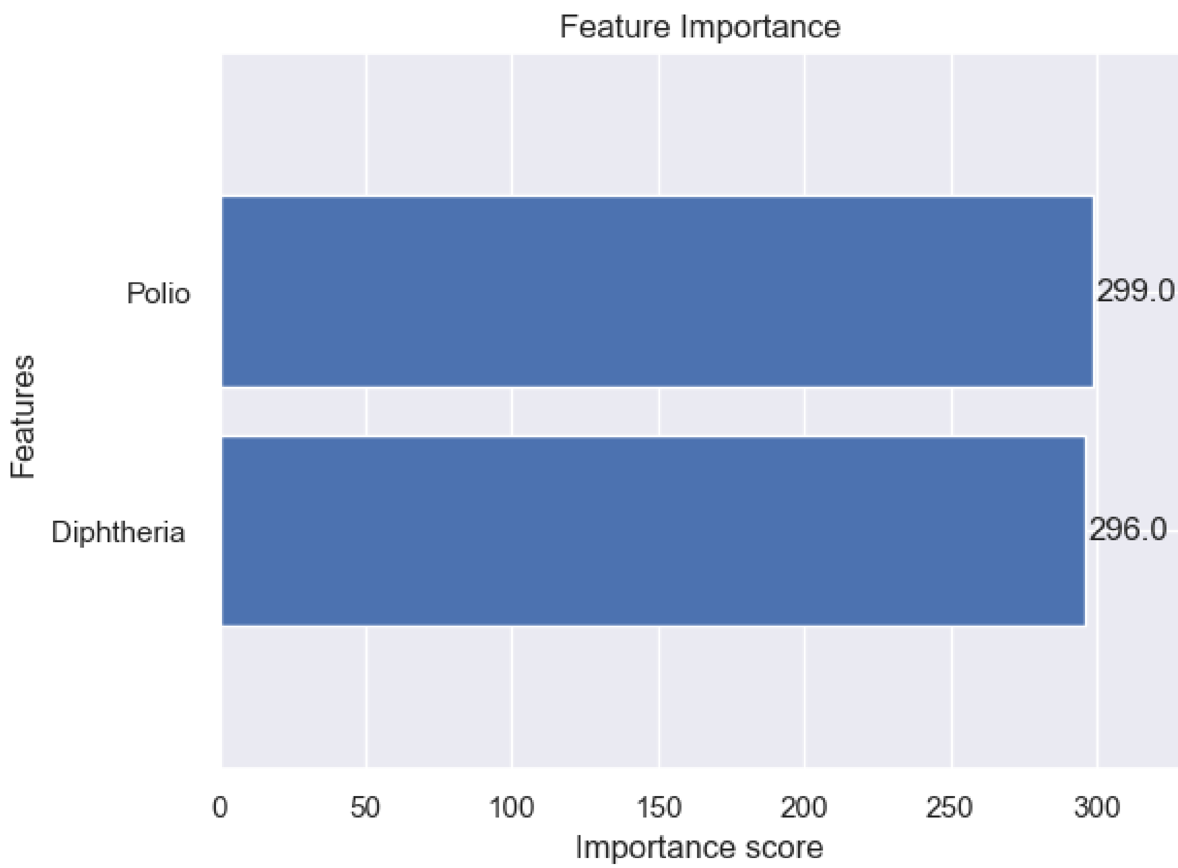
```
evaluate_xgboost_regressor(
    Schooling_ICR_developed_train, Schooling_ICR_developed_test,
LE_developed_train, LE_developed_test,
    feature_name="Schooling_ICR_developed",
    max_depth=3, n_estimators=100, learning_rate=0.1
)


evaluate_xgboost_regressor(
    Diphtheria_Polio_developed_train, Diphtheria_Polio_developed_test,
LE_developed_train, LE_developed_test,
    feature_name="Diphtheria_Polio_developed",
    max_depth=3, n_estimators=100, learning_rate=0.1
)

evaluate_xgboost_regressor(
    Thinness_Combined_developed_train,
Thinness_Combined_developed_test, LE_developed_train,
LE_developed_test ,
    feature_name="Thinness_Combined_developed",
    max_depth=3, n_estimators=100, learning_rate=0.1
)


<Figure size 1000x600 with 0 Axes>
```



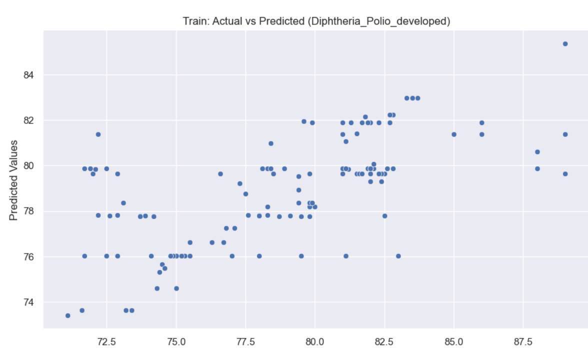

```
Train R² Score: 0.9613320140653031
Test R² Score: 0.648173699604977
Train MSE: 0.7094476382053458
Test MSE: 6.495926149229996
Train MAE: 0.6294191040039065
Test MAE: 1.6644891284760974
Regression Line Equation (Test): y = 0.6887x + 24.4646
```

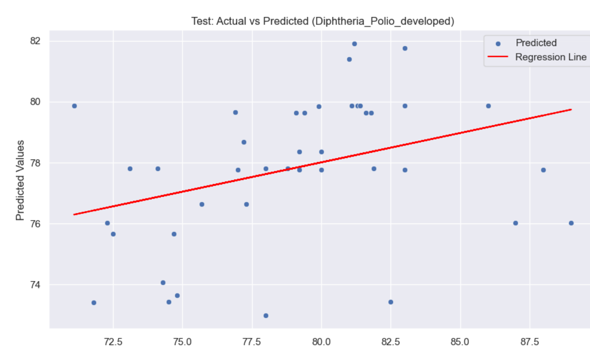



```
<Figure size 1000x600 with 0 Axes>
```

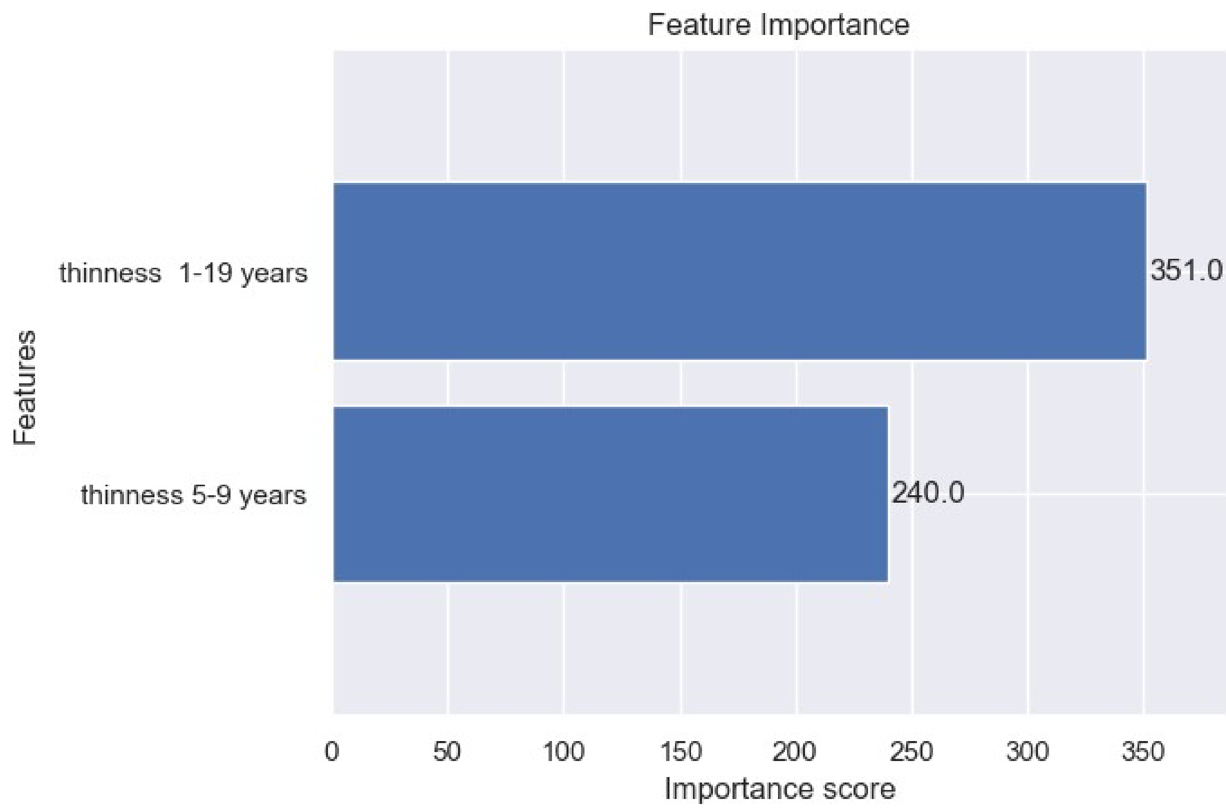



```
Train R² Score: 0.42708835188288574
Test R² Score: -0.002454188081901565
Train MSE: 10.511300390546303
Test MSE: 18.50875948288961
Train MAE: 2.317276428222656
Test MAE: 2.9224916367303755
Regression Line Equation (Test): y = 0.1927x + 62.5904
```

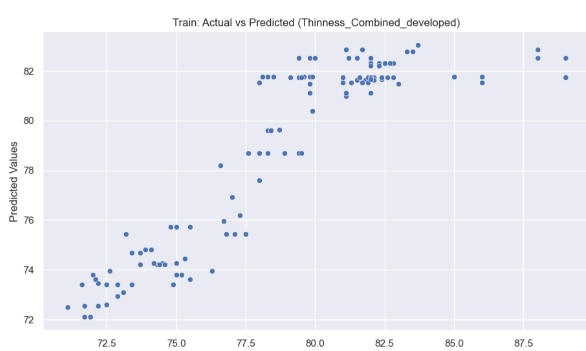


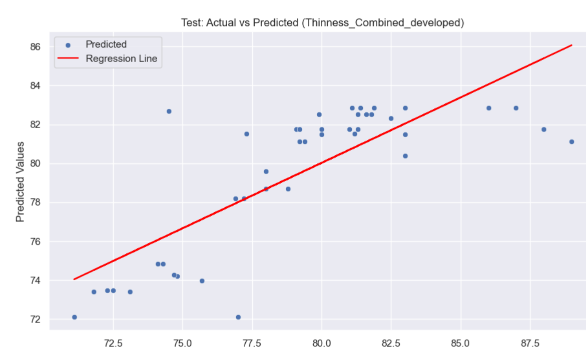



```
<Figure size 1000x600 with 0 Axes>
```




```
Train R² Score: 0.7968348458189313
Test R² Score: 0.607024518989479
Train MSE: 3.727503135094792
Test MSE: 7.255681852767455
Train MAE: 1.29321357421875
Test MAE: 1.9089945838564921
Regression Line Equation (Test): y = 0.6720x + 26.2537
```





Creating Developing Variables

```
Adult_Mortality_developing = pd.DataFrame(sortDF["Adult Mortality"])
LE_developing = pd.DataFrame(sortDF['Life expectancy '])
Adult_Mortality_developing_train, Adult_Mortality_developing_test,
```

```
LE_developing_train, LE_developing_test =
split(Adult_Mortality_developing, LE_developing, test_size=0.25,
random_state=42)

Schooling_developing = pd.DataFrame(sortDF["Schooling"])
Schooling_developing_train, Schooling_developing_test,
LE_developing_train, LE_developing_test = split(Schooling_developing,
LE_developing, test_size=0.25, random_state=42)

ICR_developing = pd.DataFrame(sortDF["Income composition of
resources"])
ICR_developing_train, ICR_developing_test, LE_developing_train,
LE_developing_test = split(ICR_developing, LE_developing,
test_size=0.25, random_state=42)

Diphtheria_developing = pd.DataFrame(sortDF["Diphtheria "])
Diphtheria_developing_train, Diphtheria_developing_test,
LE_developing_train, LE_developing_test = split(Diphtheria_developing,
LE_developing, test_size=0.25, random_state=42)

Polio_developing = pd.DataFrame(sortDF["Polio"])
Polio_developing_train, Polio_developing_test, LE_developing_train,
LE_developing_test = split(Polio_developing, LE_developing,
test_size=0.25, random_state=42)

Alcohol_developing = pd.DataFrame(sortDF["Alcohol"])
Alcohol_developing_train, Alcohol_developing_test,
LE_developing_train, LE_developing_test = split(Alcohol_developing,
LE_developing, test_size=0.25, random_state=42)


Thinness_1_19_developing = pd.DataFrame(sortDF[" thinness  1-19
years"])
Thinness_1_19_developing_train, Thinness_1_19_developing_test,
LE_developing_train, LE_developing_test = split(
    Thinness_1_19_developing, LE_developing, test_size=0.25,
random_state=42)



Thinness_5_9_developing = pd.DataFrame(sortDF[" thinness 5-9 years"])
Thinness_5_9_developing_train, Thinness_5_9_developing_test,
LE_developing_train, LE_developing_test = split(
    Thinness_5_9_developing, LE_developing, test_size=0.25,
random_state=42)
```

Creating Multi Variates for Developing

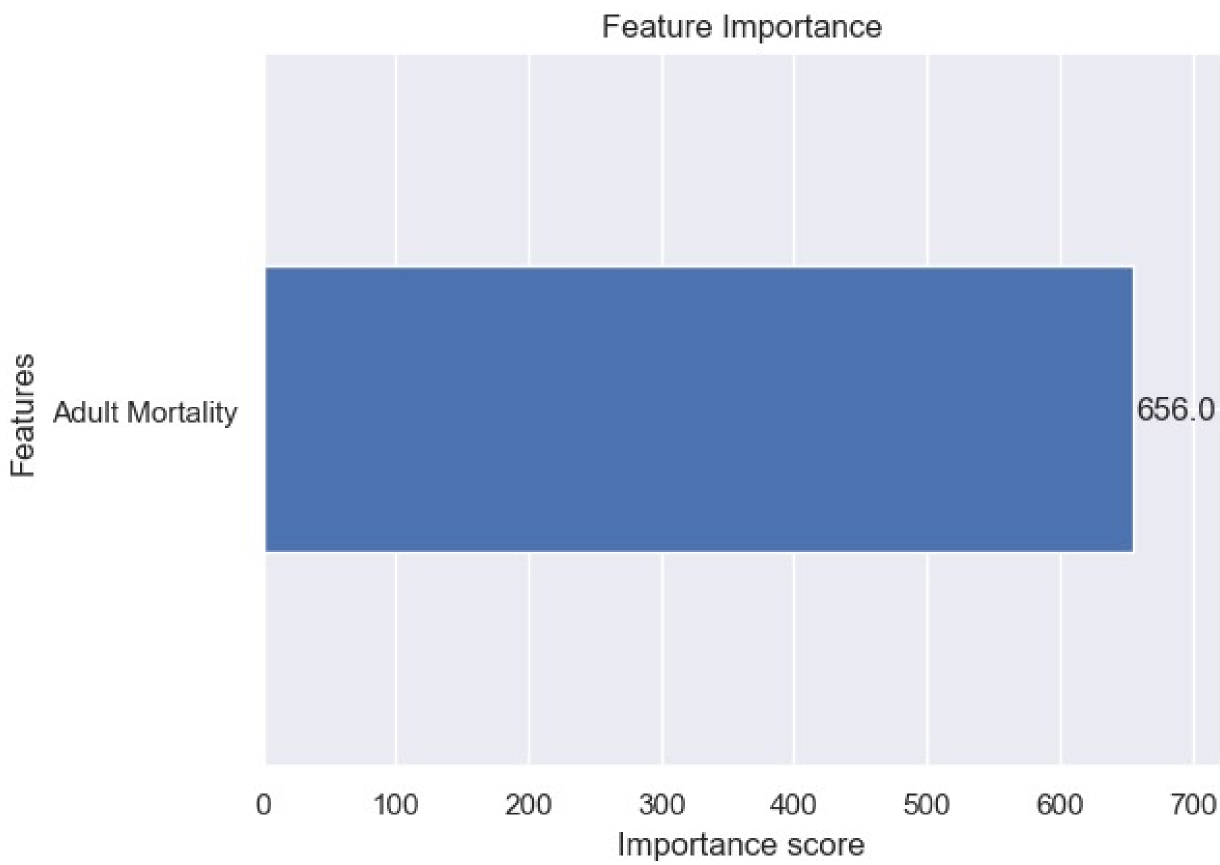
```
Schooling_ICR_developing = pd.concat([Schooling_developing,
```

```
ICR_developing], axis=1)
Schooling_ICR_developing_train, Schooling_ICR_developing_test,
LE_developing_train, LE_developing_test = split(
    Schooling_ICR_developing, LE_developing, test_size=0.25,
random_state=42
)

Diphtheria_Polio_developing= pd.concat([Diphtheria_developing,
Polio_developing], axis=1)
Diphtheria_Polio_developing_train, Diphtheria_Polio_developing_test,
LE_developing_train, LE_developing_test = split(
    Diphtheria_Polio_developing, LE_developing, test_size=0.25,
random_state=42
)

Thinness_Combined_developing = pd.concat([Thinness_1_19_developing,
Thinness_5_9_developing], axis=1)


Thinness_Combined_developing_train, Thinness_Combined_developing_test,
LE_developing_train, LE_developing_test = split(
    Thinness_Combined_developing, LE_developing, test_size=0.25,
random_state=42
)
```

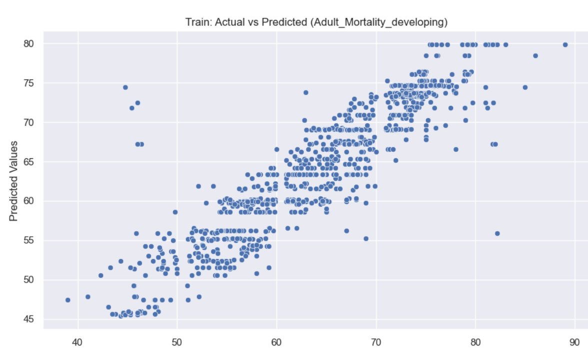
XGBoost for developing

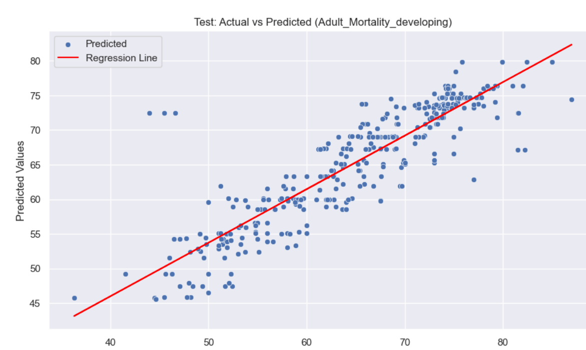
```
evaluate_xgboost_regressor(Adult_Mortality_developing_train,
Adult_Mortality_developing_test, LE_developing_train,
LE_developing_test,

feature_name="Adult_Mortality_developing",
                                 max_depth=3, n_estimators=100,
learning_rate=0.1)
```

```
<Figure size 1000x600 with 0 Axes>
```



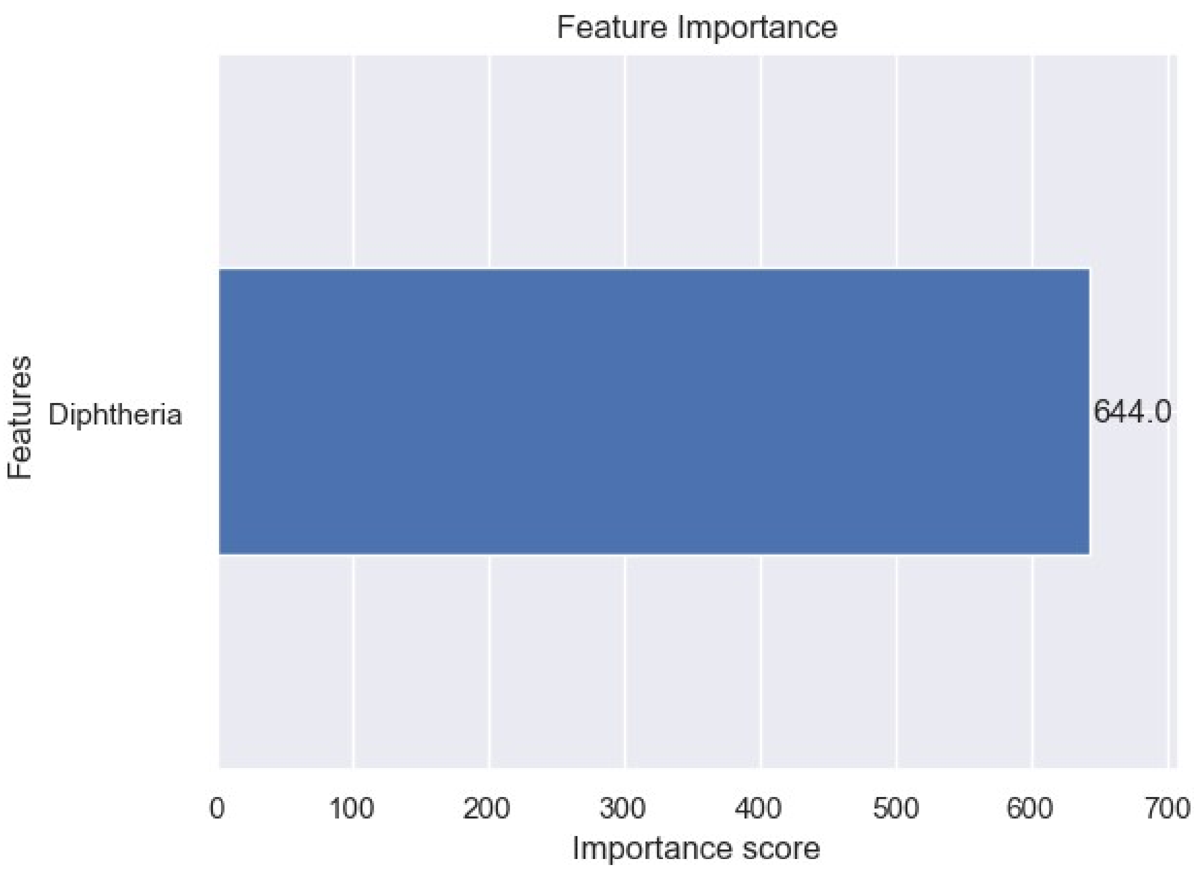

```
Train R² Score: 0.838146612459261
Test R² Score: 0.7932584384106999
Train MSE: 13.586073413245845
Test MSE: 19.609030150654046
Train MAE: 2.5105868307959955
Test MAE: 2.978116190534813
Regression Line Equation (Test): y = 0.7733x + 15.0619
```



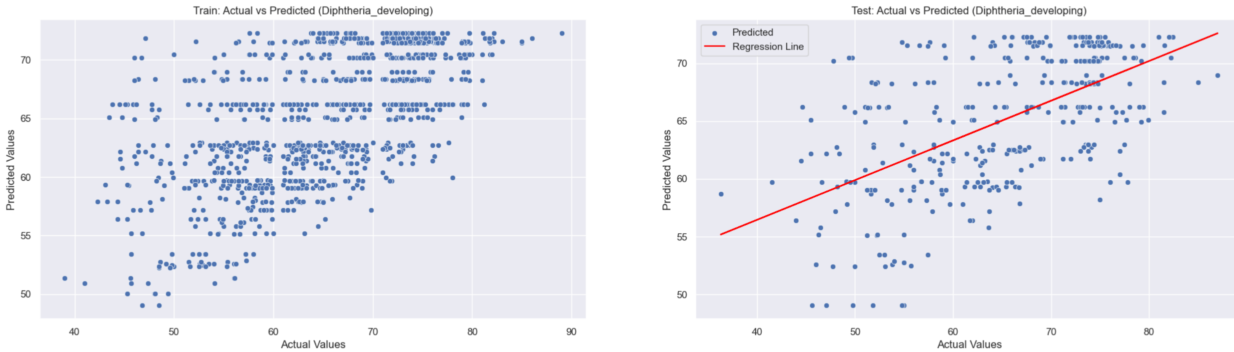



```
evaluate_xgboost_regressor(Diphtheria_developing_train,
                                 Diphtheria_developing_test,
                                 LE_developing_train,
```

```
                                 LE_developing_test,
                                 feature_name="Diphtheria_developing",

                                 max_depth=3, n_estimators=100,
learning_rate=0.1)

<Figure size 1000x600 with 0 Axes>
```



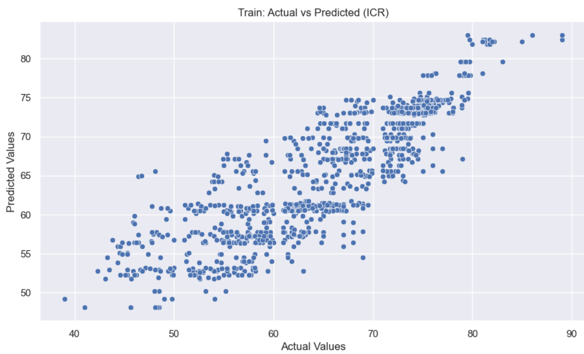

```
Train R² Score: 0.39615328822193885
Test R² Score: 0.33766209845791617
Train MSE: 50.68726630450597
Test MSE: 62.821446164078104
Train MAE: 5.562121327958698
Test MAE: 6.290816474028418
Regression Line Equation (Test): y = 0.3437x + 42.6970
```

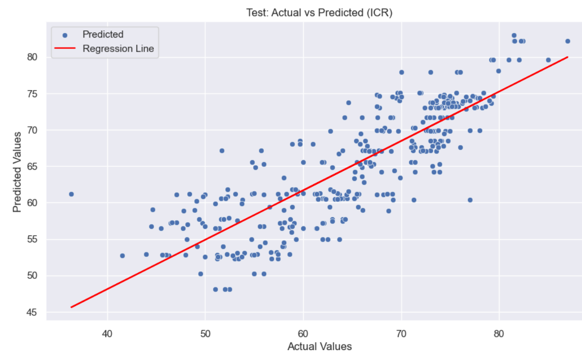



```
evaluate_xgboost_regressor(ICR_developing_train, ICR_developing_test,
LE_developing_train, LE_developing_test,
                                 feature_name="ICR",
                                 max_depth=3, n_estimators=100,
learning_rate=0.1)
```

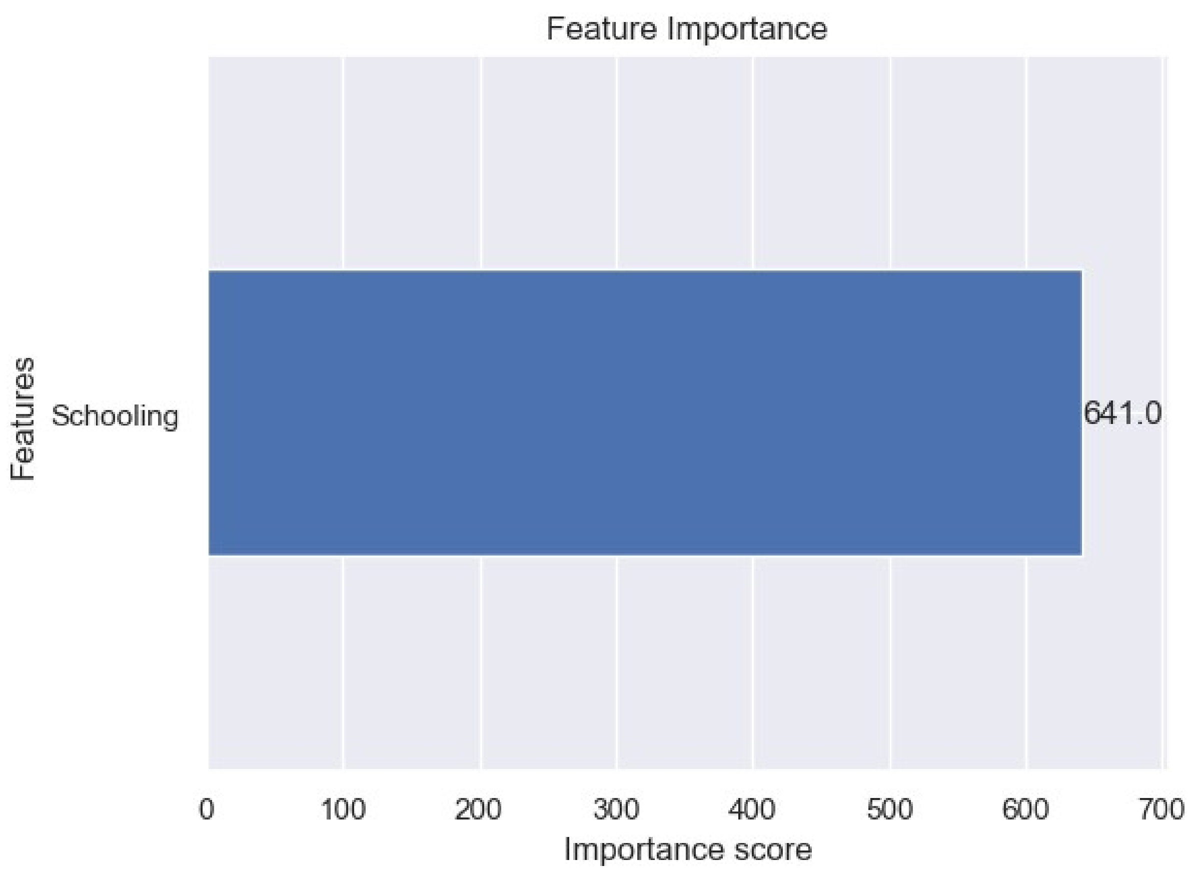
```
<Figure size 1000x600 with 0 Axes>
```


```
Train R² Score: 0.7501064358473697
Test R² Score: 0.7053840512226066
Train MSE: 20.976220267374675
Test MSE: 27.943742796699716
Train MAE: 3.4794821667919327
Test MAE: 4.094929969074369
Regression Line Equation (Test): y = 0.6784x + 20.9653
```



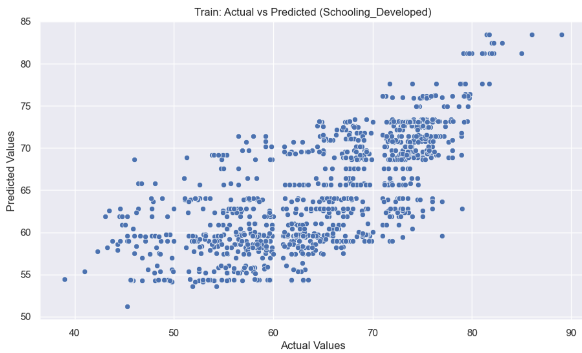


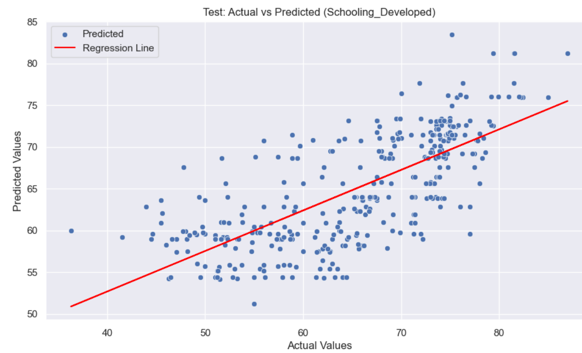

```
evaluate_xgboost_regressor(Schooling_developing_train,
Schooling_developing_test, LE_developing_train, LE_developing_test,
                                 feature_name="Schooling_Developed",
                                 max_depth=3, n_estimators=100,
learning_rate=0.1)

<Figure size 1000x600 with 0 Axes>
```



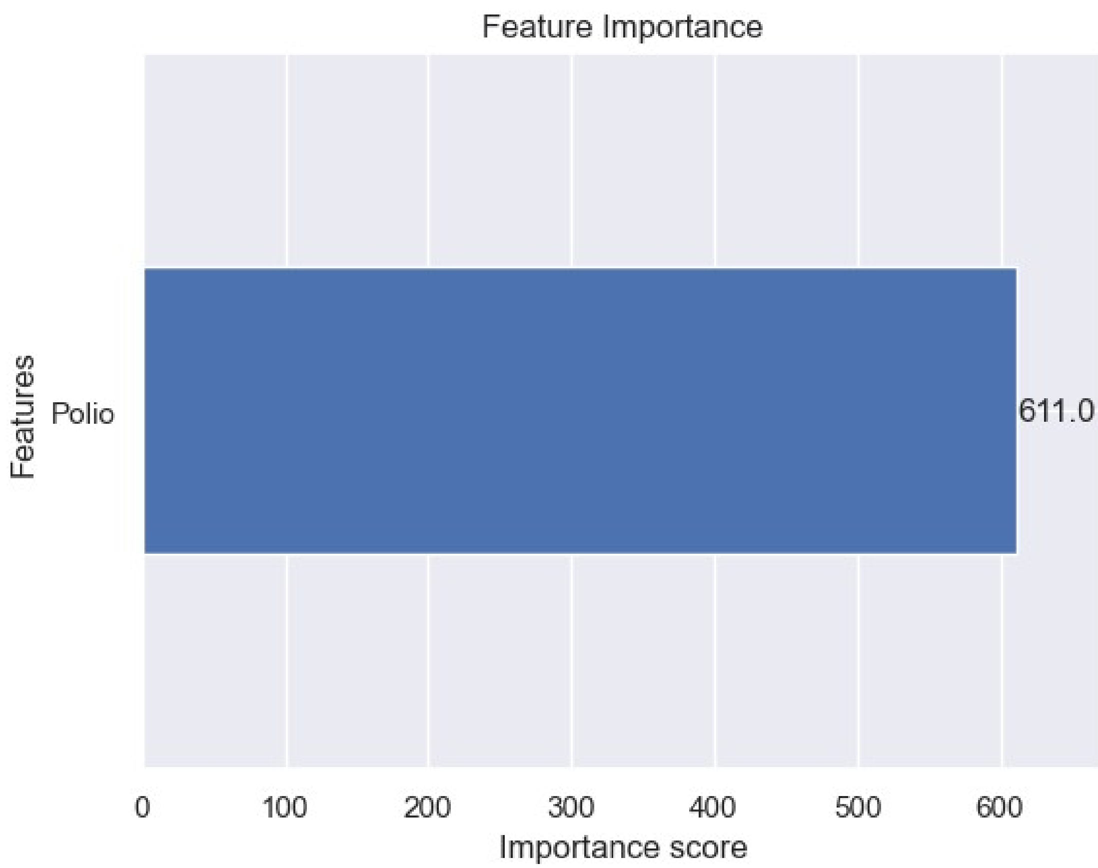

```
Train R² Score: 0.5425655479247968
Test R² Score: 0.5113108423471928
Train MSE: 38.397330708183866
```

```
Test MSE: 46.35120462980762
Train MAE: 4.778433273012276
Test MAE: 5.462983580419092
Regression Line Equation (Test): y = 0.4852x + 33.2816
```

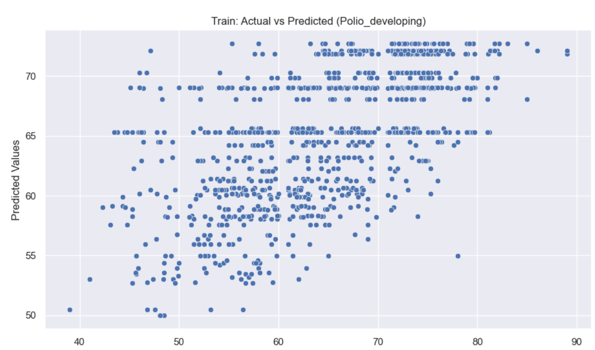


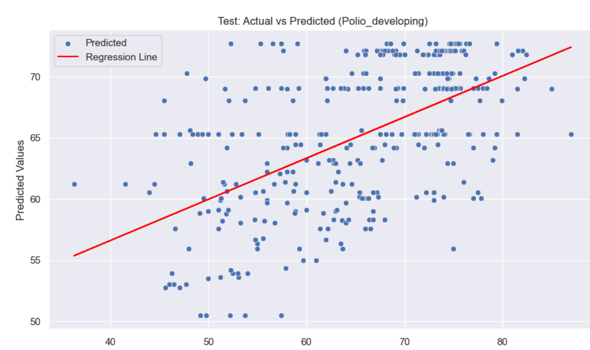



```
evaluate_xgboost_regressor(Polio_developing_train,
Polio_developing_test, LE_developing_train, LE_developing_test,
                                 feature_name="Polio_developing",
                                 max_depth=3, n_estimators=100,
learning_rate=0.1)

<Figure size 1000x600 with 0 Axes>
```




```
Train R² Score: 0.3839192162044358
Test R² Score: 0.3127572778686786
Train MSE: 51.71420187316002
Test MSE: 65.18361937239088
Train MAE: 5.645092966157305
Test MAE: 6.3991544556009865
Regression Line Equation (Test): y = 0.3368x + 43.1238
```

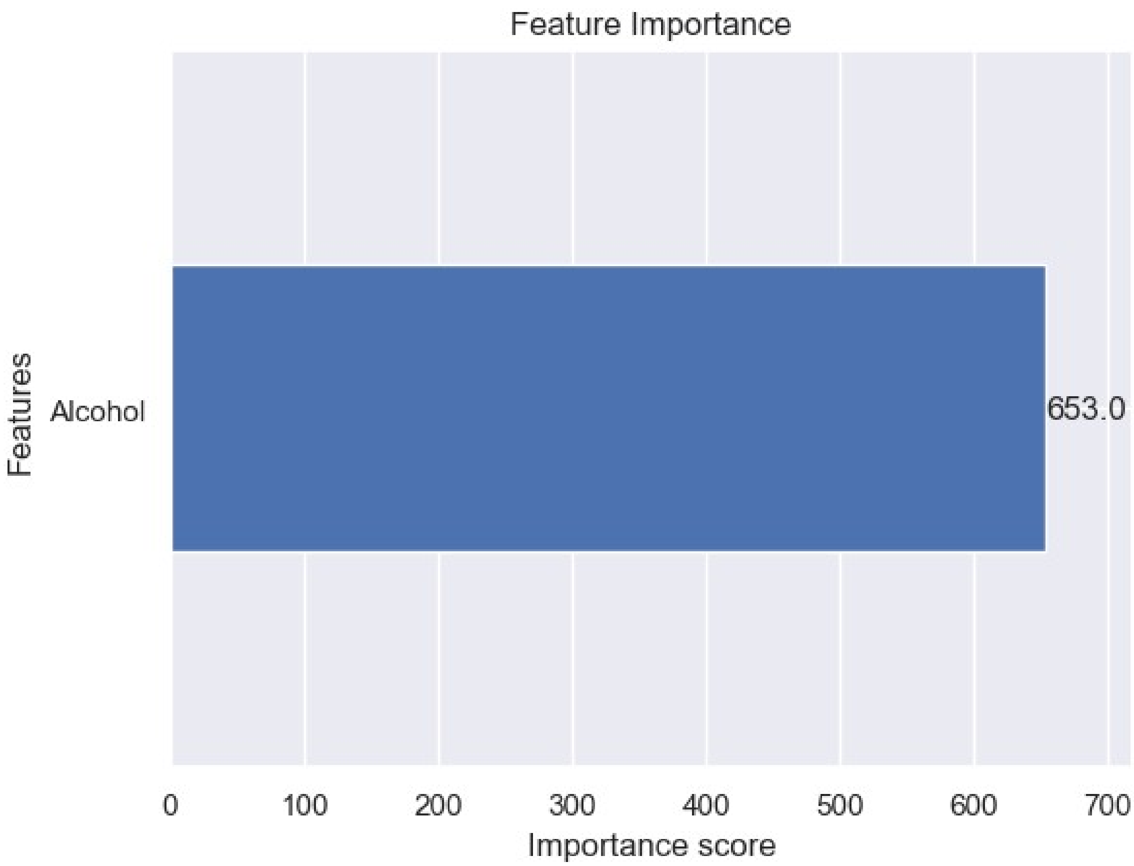




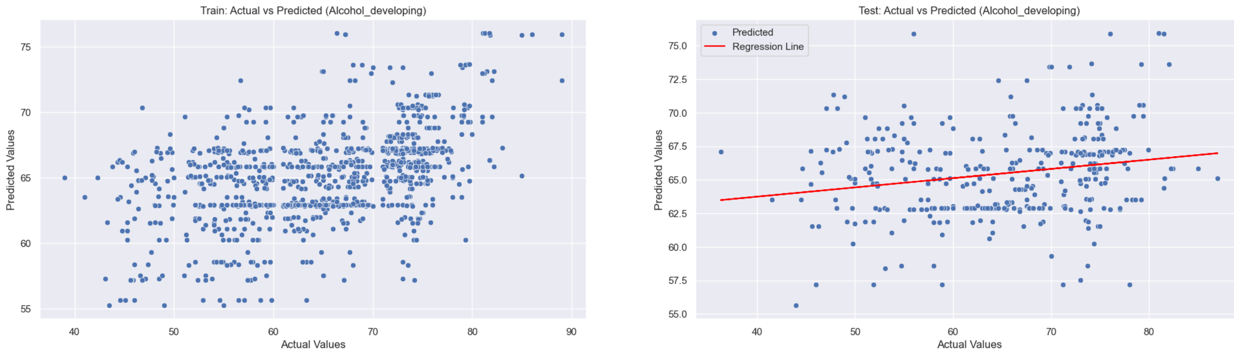

```
evaluate_xgboost_regressor(Alcohol_developing_train,
Alcohol_developing_test, LE_developing_train, LE_developing_test,
                                 feature_name="Alcohol_developing",
```

```
                                   max_depth=3, n_estimators=100,
learning_rate=0.1)
```

```
<Figure size 1000x600 with 0 Axes>
```

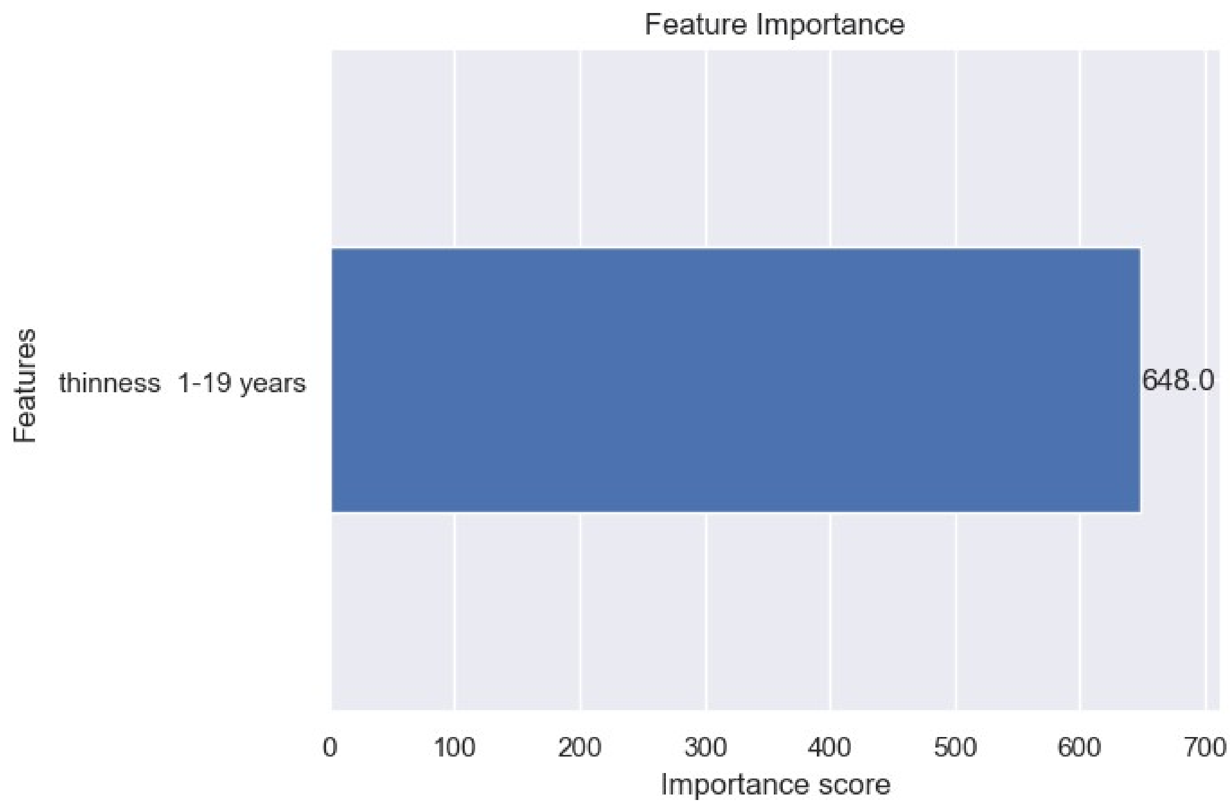



```
Train R² Score: 0.21950581678222691
Test R² Score: 0.023885279101521162
Train MSE: 65.51516426641982
Test MSE: 92.58255981745548
Train MAE: 6.685849127503308
Test MAE: 7.862697121509412
Regression Line Equation (Test): y = 0.0690x + 60.9889
```

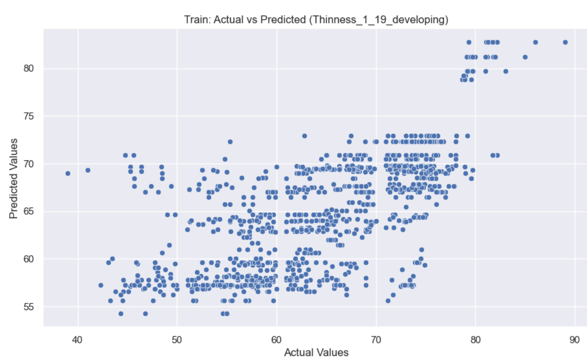


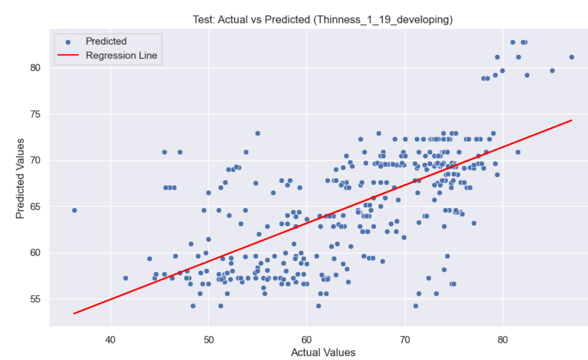

```python
evaluate_xgboost_regressor(
    Thinness_1_19_developing_train, Thinness_1_19_developing_test,
LE_developing_train, LE_developing_test,
    feature_name="Thinness_1_19_developing",
    max_depth=3, n_estimators=100, learning_rate=0.1
)

evaluate_xgboost_regressor(
    Thinness_5_9_developing_train, Thinness_5_9_developing_test,
LE_developing_train, LE_developing_test,
    feature_name="Thinness_5_9_developing",
    max_depth=3, n_estimators=100, learning_rate=0.1
)
```

```
<Figure size 1000x600 with 0 Axes>
```

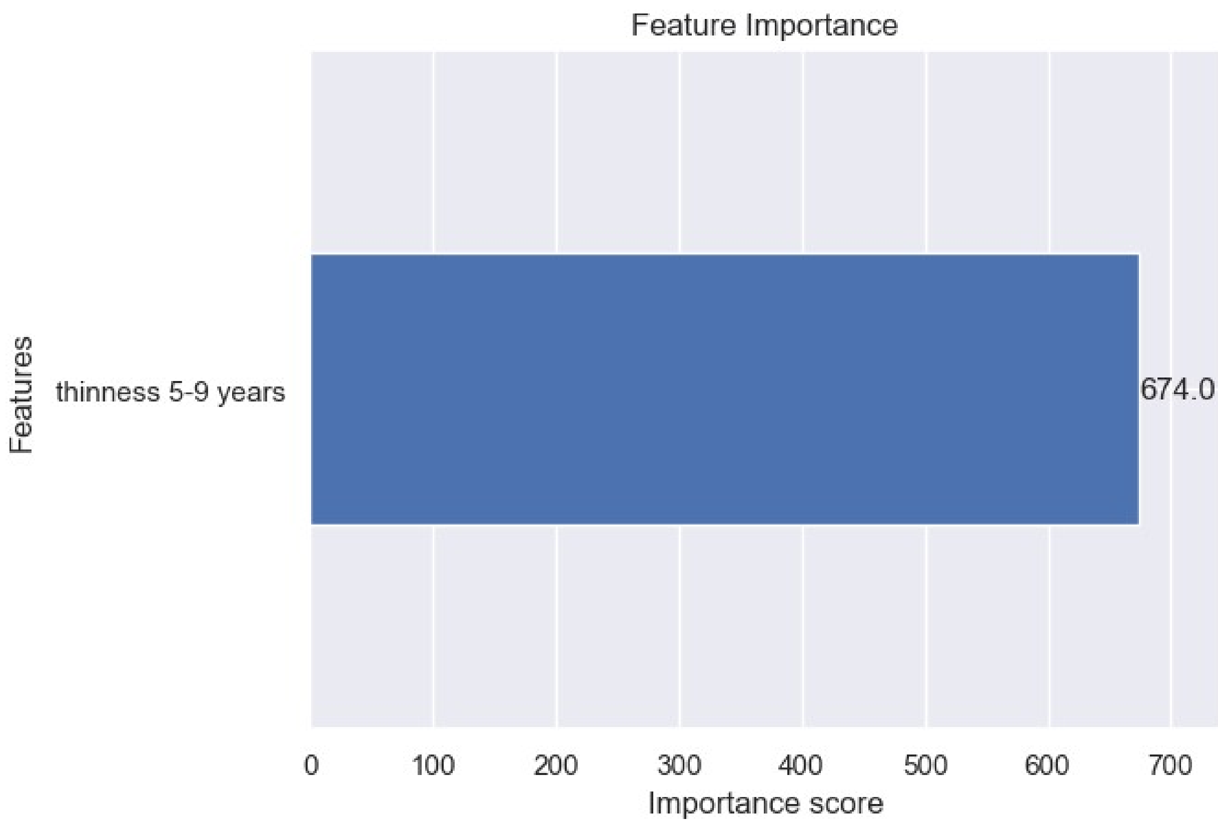



```
Train R² Score: 0.45914716862455407
Test R² Score: 0.43022294947273265
Train MSE: 45.399521038626126
Test MSE: 54.04223164926586
Train MAE: 5.110470268516576
Test MAE: 5.511168465330647
Regression Line Equation (Test): y = 0.4120x + 38.4496
```

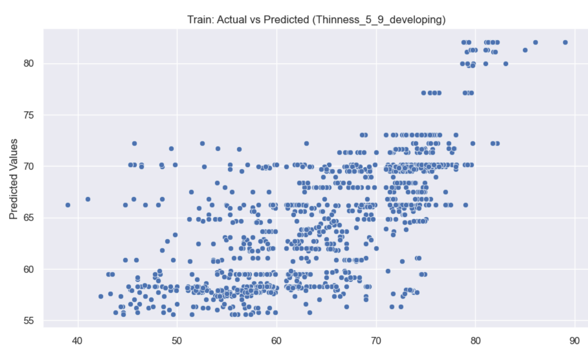


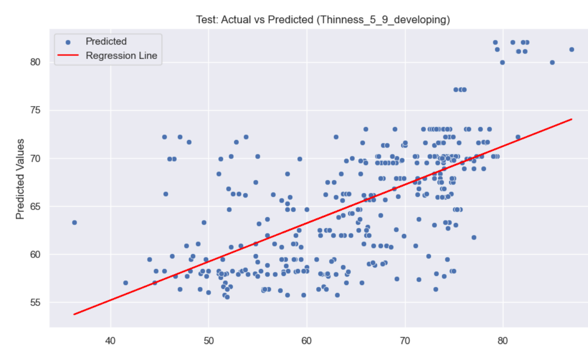



```
<Figure size 1000x600 with 0 Axes>
```




```
Train R² Score: 0.4594443426568984
Test R² Score: 0.4065507019500968
Train MSE: 45.3745760666284
Test MSE: 56.28749772850367
Train MAE: 5.101452428841208
Test MAE: 5.646327395344591
Regression Line Equation (Test): y = 0.4007x + 39.1722
```

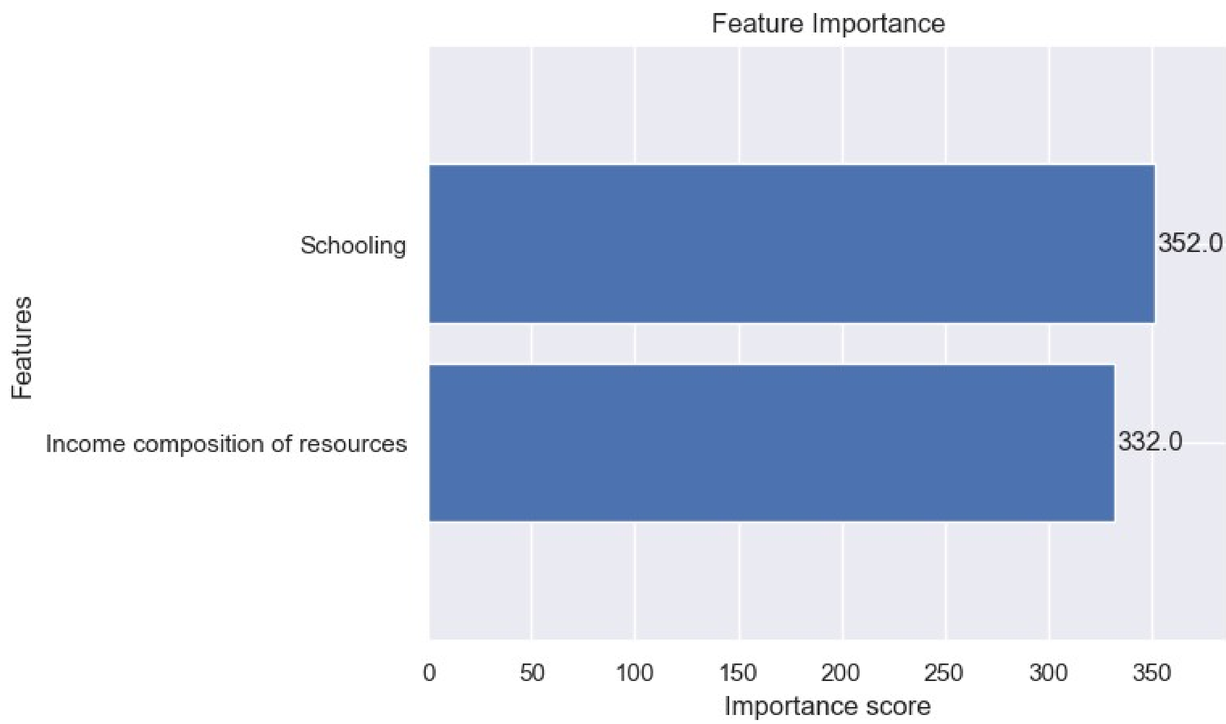




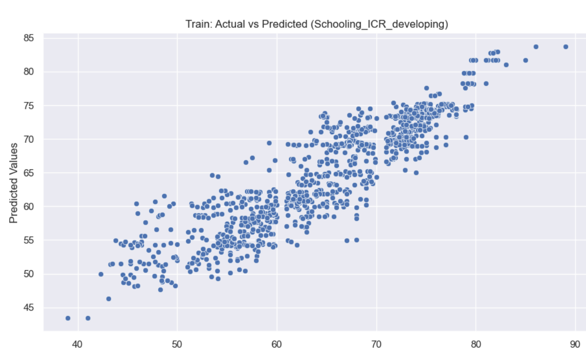
XGBoost for developing multi-variates

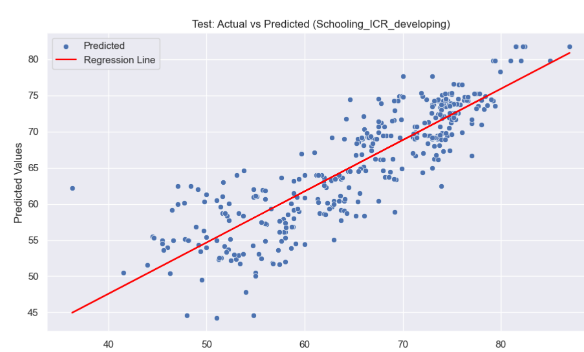
```
evaluate_xgboost_regressor(Schooling_ICR_developing_train,
Schooling_ICR_developing_test, LE_developing_train,
LE_developing_test,
```

```
feature_name="Schooling_ICR_developing",
                                 max_depth=3, n_estimators=100,
learning_rate=0.1)


<Figure size 1000x600 with 0 Axes>
```



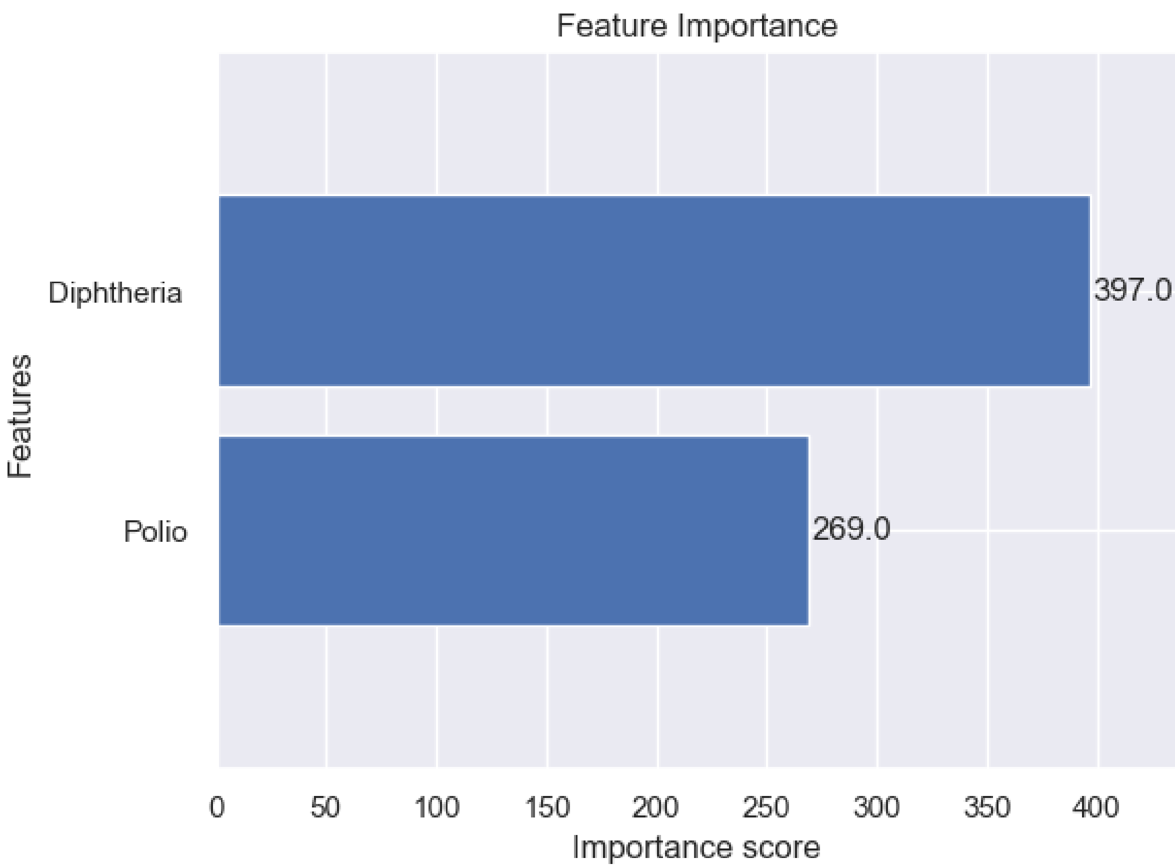

```
Train R² Score: 0.8279667762290193
Test R² Score: 0.7463400952854518
Train MSE: 14.440575159921204
Test MSE: 24.05914263838587
Train MAE: 2.885169022920116
Test MAE: 3.734753923713317
Regression Line Equation (Test): y = 0.7085x + 19.2261
```



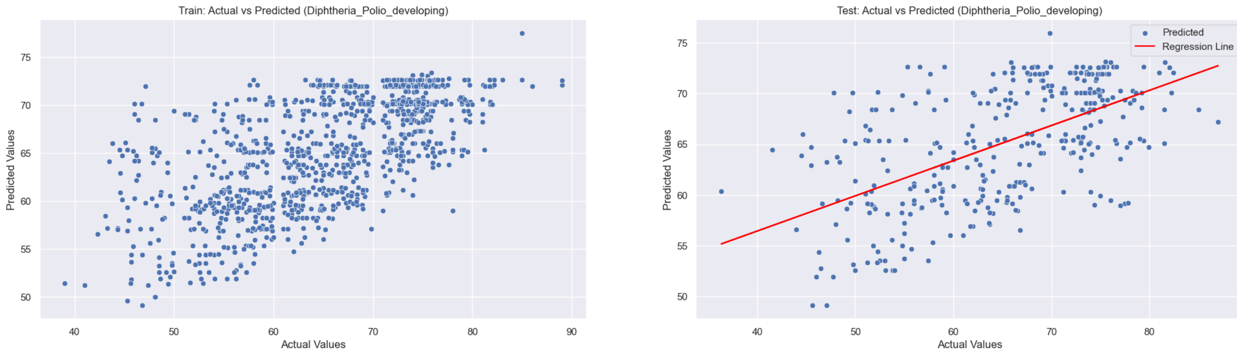


```
evaluate_xgboost_regressor(Diphtheria_Polio_developing_train,
Diphtheria_Polio_developing_test, LE_developing_train,
LE_developing_test,

feature_name="Diphtheria_Polio_developing",
                                 max_depth=3, n_estimators=100,
learning_rate=0.1)
```

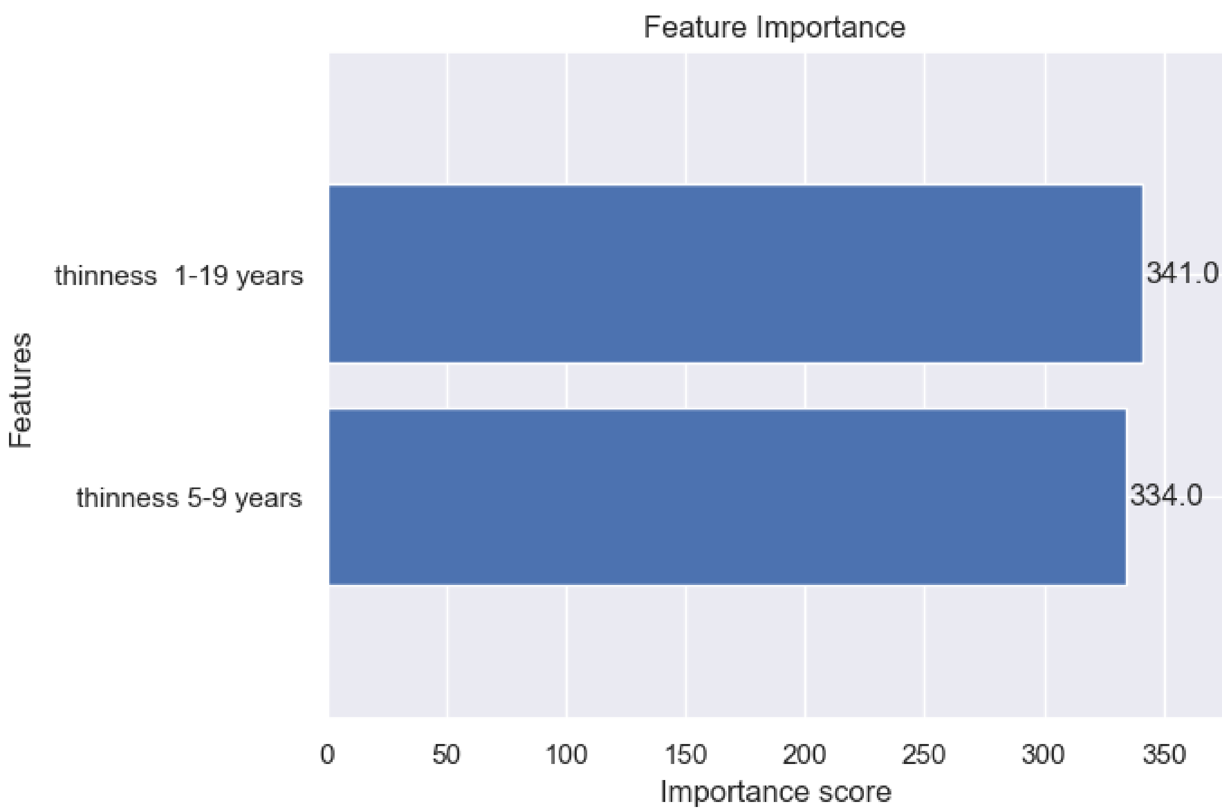
```
<Figure size 1000x600 with 0 Axes>
```




```
Train R² Score: 0.442045651509845
Test R² Score: 0.33886969939983536
Train MSE: 46.835032957953956
Test MSE: 62.70690759187223
Train MAE: 5.3311076724540545
Test MAE: 6.21170887285184
Regression Line Equation (Test): y = 0.3470x + 42.5705
```

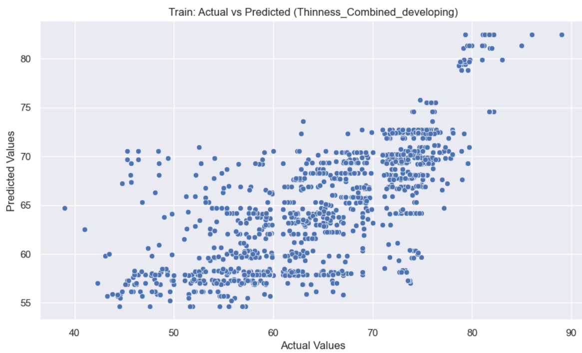



```
evaluate_xgboost_regressor(Thinness_Combined_developing_train,
Thinness_Combined_developing_test, LE_developing_train,
LE_developing_test,

feature_name="Thinness_Combined_developing",
                                max_depth=3, n_estimators=100,
learning_rate=0.1)

<Figure size 1000x600 with 0 Axes>
```




```
Train R² Score: 0.5174830158444479
Test R² Score: 0.42912733946623416
Train MSE: 40.502773957852895
```

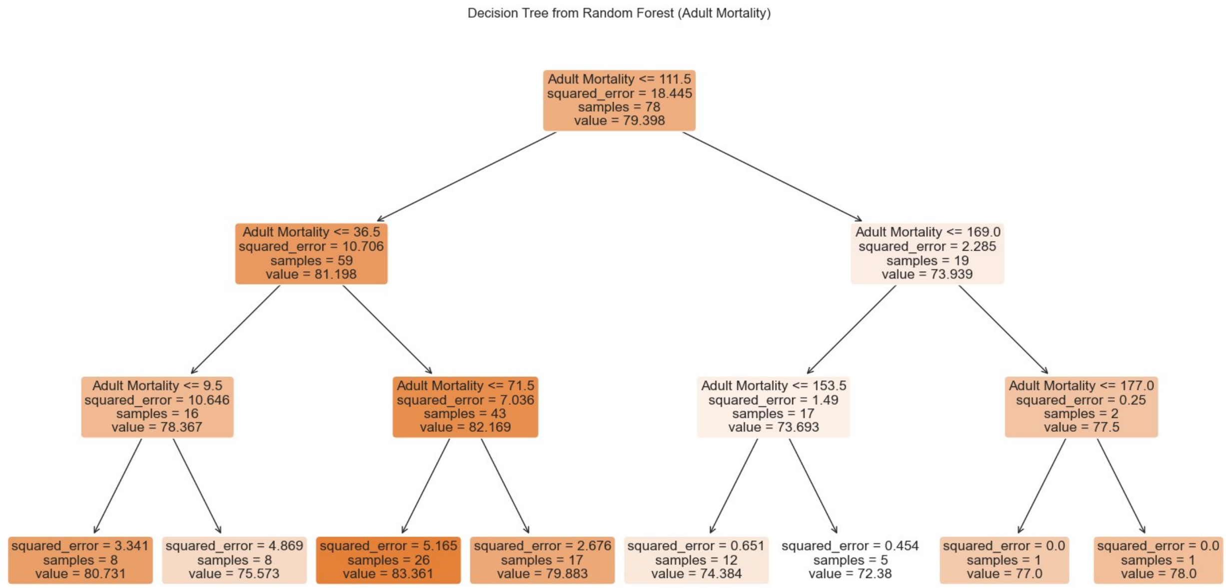
```
Test MSE: 54.14614810169871
Train MAE: 4.757943869945342
Test MAE: 5.344392758118195
Regression Line Equation (Test): y = 0.4233x + 37.7406
```



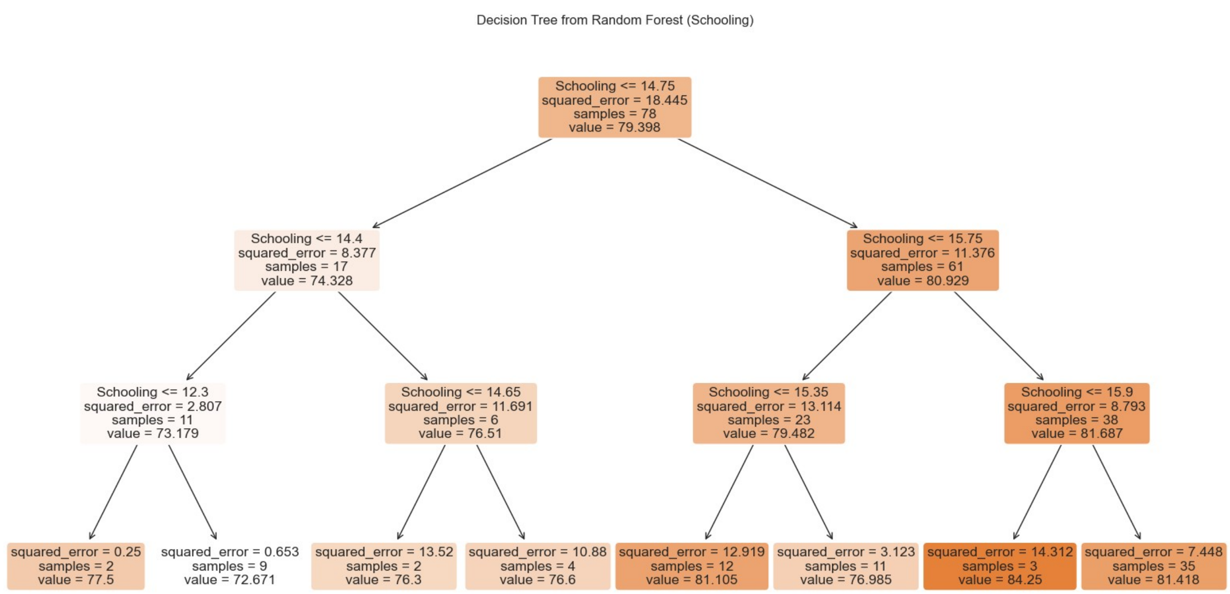
Random forest for developed

```
# Adult Mortality
evaluate_random_forest_regressor(
    Adult_Mortality_developed_train, Adult_Mortality_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Adult Mortality",
    max_depth=3, n_estimators=100
)

# Schooling
evaluate_random_forest_regressor(
    Schooling_developed_train, Schooling_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Schooling",
    max_depth=3, n_estimators=100
)

# Income Composition of Resources (ICR)
evaluate_random_forest_regressor(
    ICR_developed_train, ICR_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="ICR",
    max_depth=3, n_estimators=100
)

# Diphtheria
evaluate_random_forest_regressor(
    Diphtheria_developed_train, Diphtheria_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Diphtheria",
```

```
    max_depth=3, n_estimators=100
)

# Alcohol
evaluate_random_forest_regressor(
    Alcohol_developed_train, Alcohol_developed_test,
    LE_developed_train, LE_developed_test,
    feature_name="Alcohol",
    max_depth=3, n_estimators=100
)

# Polio
evaluate_random_forest_regressor(
    Polio_developed_train, Polio_developed_test, LE_developed_train,
LE_developed_test,
    feature_name="Polio",
    max_depth=3, n_estimators=100
)


# Evaluate Random Forest for Thinness_1_19_developed
evaluate_random_forest_regressor(
    Thinness_1_19_developed_train, Thinness_1_19_developed_test,
LE_developed_train, LE_developed_test,
    feature_name="Thinness_1_19_developed",
    max_depth=3, n_estimators=100
)

# Evaluate Random Forest for Thinness_5_9_developed
evaluate_random_forest_regressor(
    Thinness_5_9_developed_train, Thinness_5_9_developed_test,
LE_developed_train, LE_developed_test,
    feature_name="Thinness_5_9_developed",
    max_depth=3, n_estimators=100
)
```



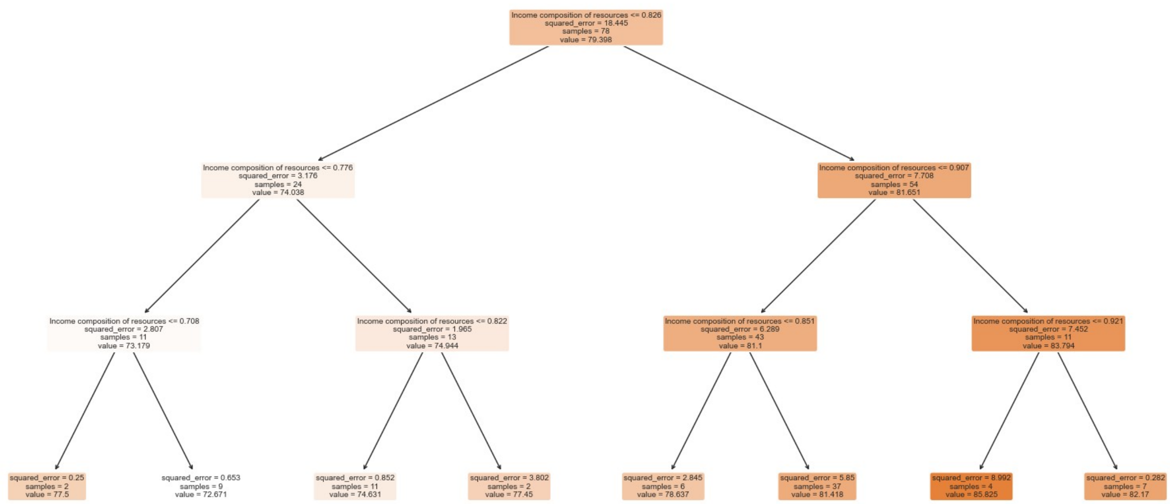

```
Train R² Score (Adult Mortality): 0.8358962599052406
Test R² Score (Adult Mortality): 0.6813880236231769
Train MSE (Adult Mortality): 3.010837208524587
Test MSE (Adult Mortality): 5.882675247644259
Train MAE (Adult Mortality): 1.2078948182802536
Test MAE (Adult Mortality): 1.6974284627044065
```



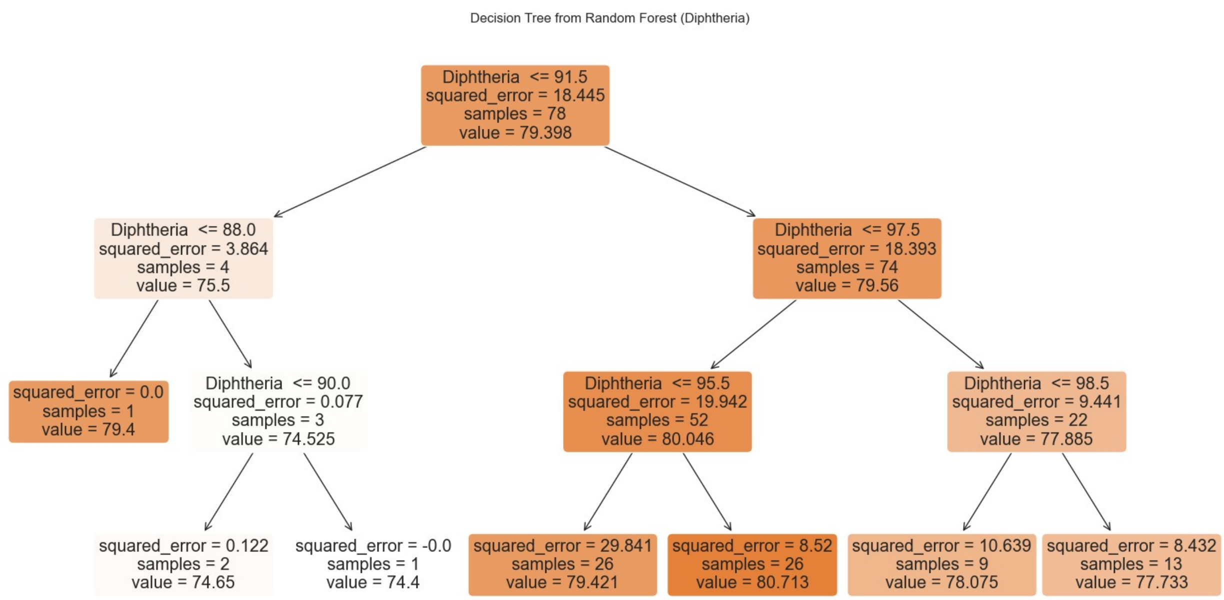

```
Train R² Score (Schooling): 0.576132563631735
Test R² Score (Schooling): 0.5440691077463705
Train MSE (Schooling): 7.7767627243753195
```

```
Test MSE (Schooling): 8.418055733487776
Train MAE (Schooling): 2.0778825545603254
Test MAE (Schooling): 2.1517143951100186
```

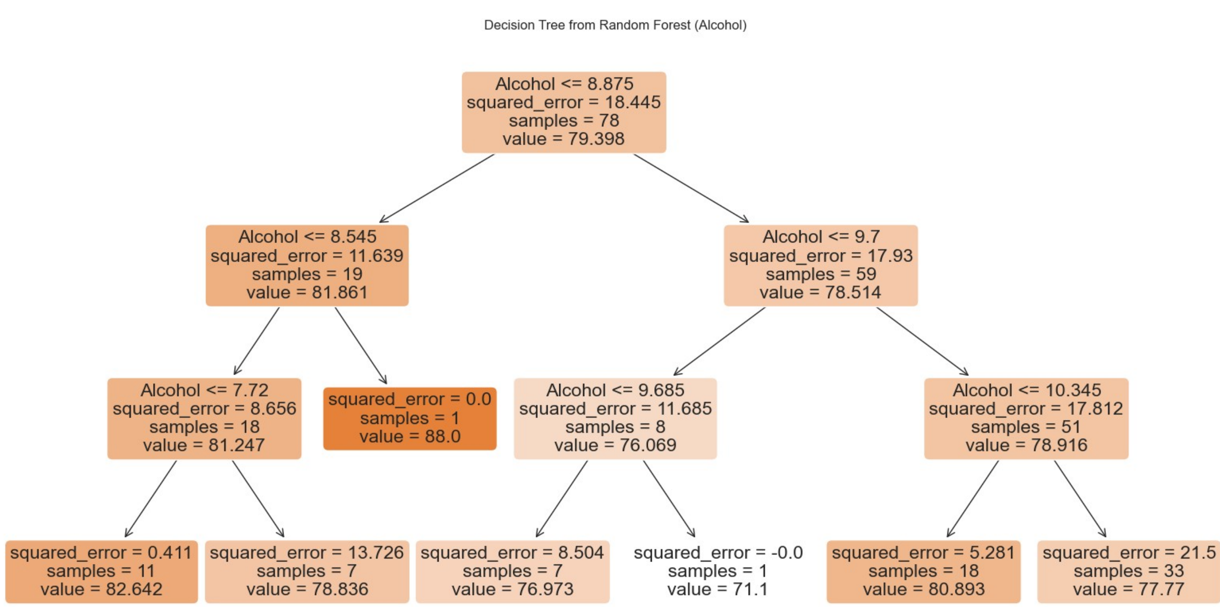
Decision Tree from Random Forest (ICR)




```
Train R² Score (ICR): 0.7911248501866684
Test R² Score (ICR): 0.6833460612789666
Train MSE (ICR): 3.832265325768829
Test MSE (ICR): 5.8465231237264605
Train MAE (ICR): 1.478390966031627
Test MAE (ICR): 1.7590755520443373
```

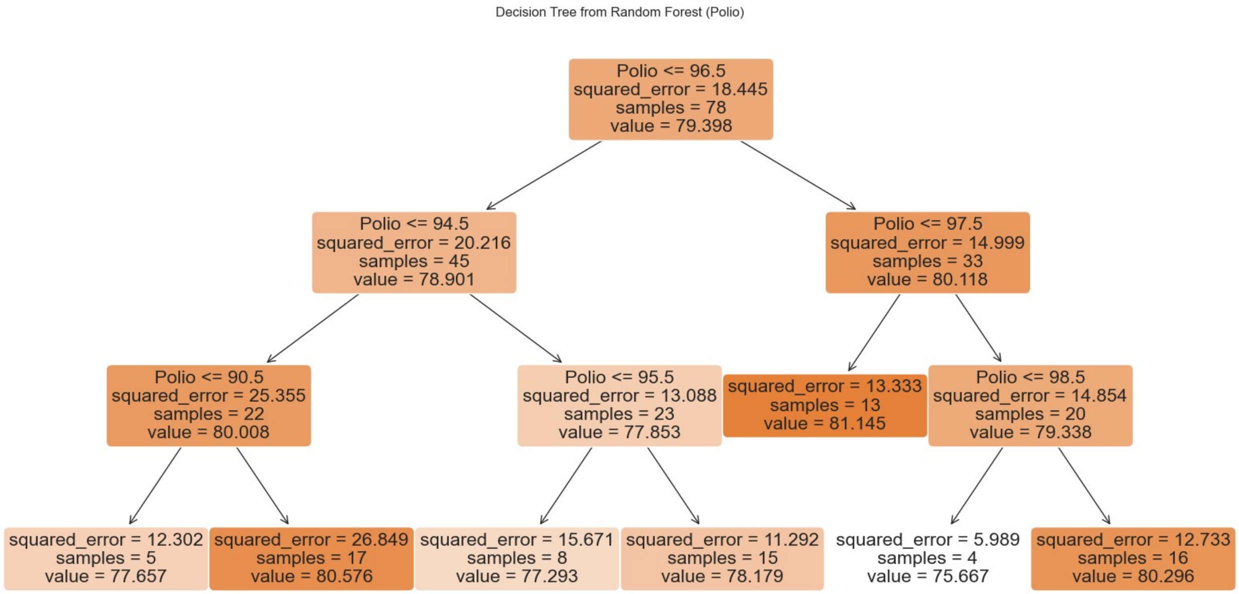



```
Train R² Score (Diphtheria): 0.1423495476615334
Test R² Score (Diphtheria): -0.013541329400863278
Train MSE (Diphtheria): 15.735448151989209
Test MSE (Diphtheria): 18.71346632582087
Train MAE (Diphtheria): 3.027448316435783
Test MAE (Diphtheria): 3.132893943586316
```

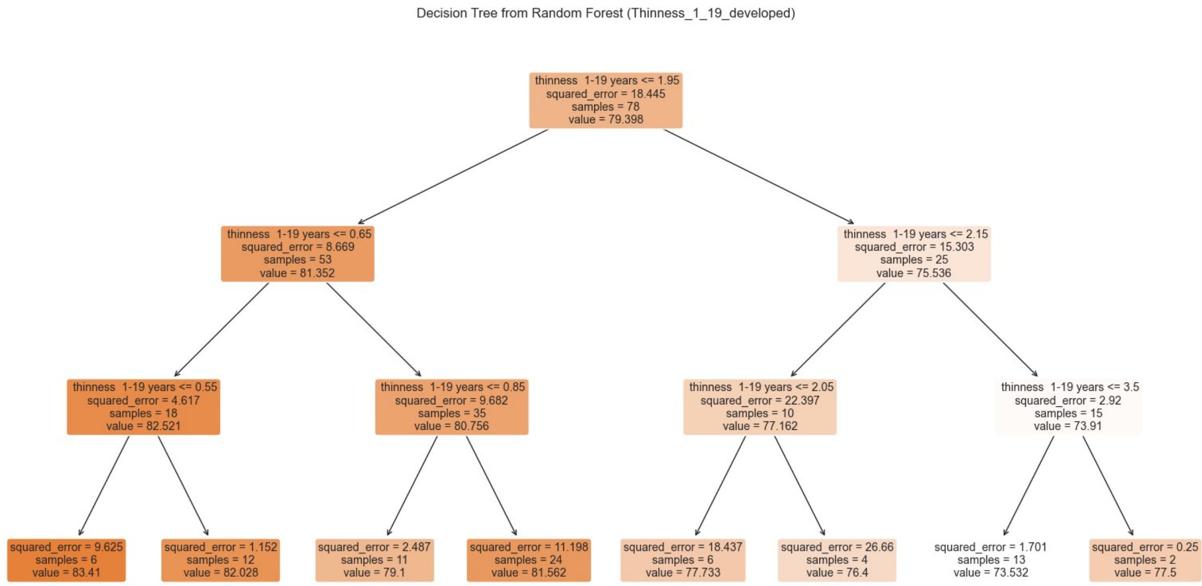



```
Train R² Score (Alcohol): 0.29620643840145344
Test R² Score (Alcohol): -0.010104414592446709
Train MSE (Alcohol): 12.912611505120813
```

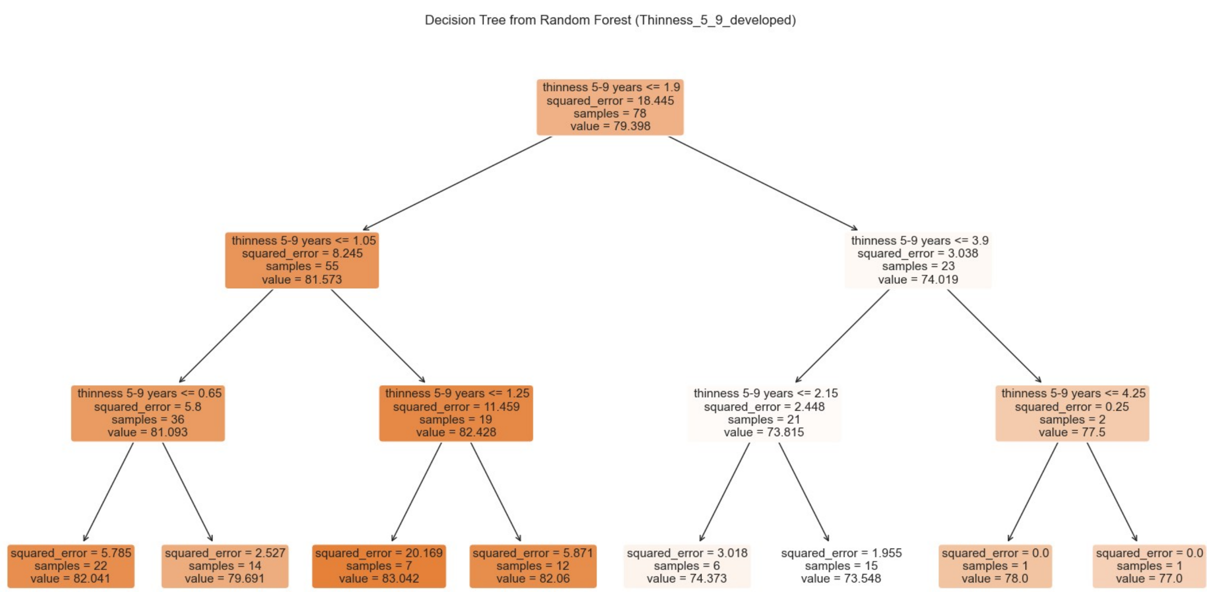
```
Test MSE (Alcohol): 18.650009032401925
Train MAE (Alcohol): 2.8581483771409952
Test MAE (Alcohol): 3.0934831602789954
```




```
Train R² Score (Polio): 0.08729858849667449
Test R² Score (Polio): -0.001542664068816313
Train MSE (Polio): 16.74547678462619
Test MSE (Polio): 18.491929607847283
Train MAE (Polio): 3.3303717472818124
Test MAE (Polio): 3.262144866498962
```




```
Train R² Score (Thinness_1_19_developed): 0.5982453976026149
Test R² Score (Thinness_1_19_developed): 0.599194826403846
Train MSE (Thinness_1_19_developed): 7.3710550709909
Test MSE (Thinness_1_19_developed): 7.400244964593774
Train MAE (Thinness_1_19_developed): 2.0290406335984112
Test MAE (Thinness_1_19_developed): 2.0683449138033216
```



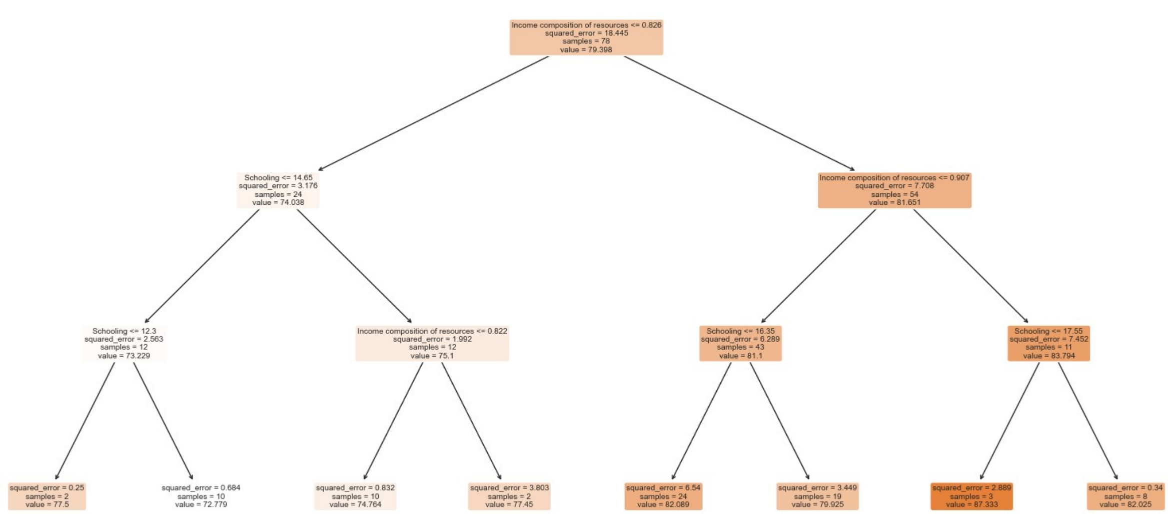

```
Train R² Score (Thinness_5_9_developed): 0.685918218739164
Test R² Score (Thinness_5_9_developed): 0.5649312298017095
Train MSE (Thinness_5_9_developed): 5.7625079903343694
```

```
Test MSE (Thinness_5_9_developed): 8.032869054619406
Train MAE (Thinness_5_9_developed): 1.794932596787905
Test MAE (Thinness_5_9_developed): 2.1379590377588715
```

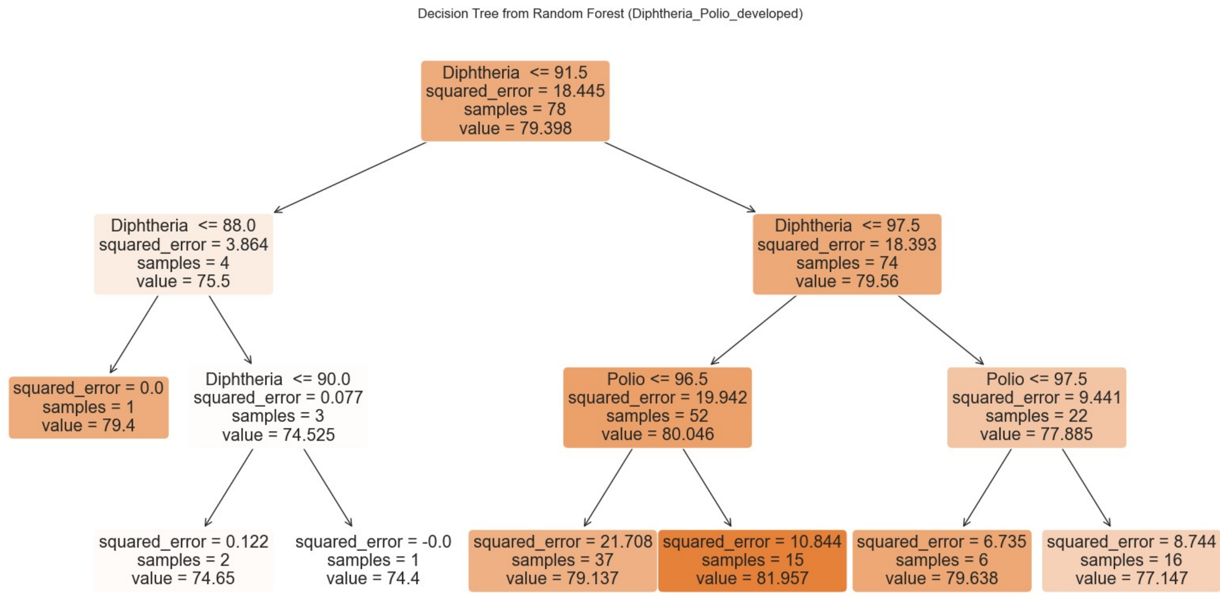
Random forest for developed multi-variate

```python
# Evaluate Random Forest for Schooling_ICR_developed
evaluate_random_forest_regressor(
    Schooling_ICR_developed_train, Schooling_ICR_developed_test,
LE_developed_train, LE_developed_test,
    feature_name="Schooling_ICR_developed",
    max_depth=3, n_estimators=100
)

# Evaluate Random Forest for Diphtheria_Polio_developed
evaluate_random_forest_regressor(
    Diphtheria_Polio_developed_train, Diphtheria_Polio_developed_test,
LE_developed_train, LE_developed_test,
    feature_name="Diphtheria_Polio_developed",
    max_depth=3, n_estimators=100
)

# Evaluate Random Forest for Thinness_Combined_developed
evaluate_random_forest_regressor(
    Thinness_Combined_developed_train,
Thinness_Combined_developed_test, LE_developed_train,
LE_developed_test,
    feature_name="Thinness_Combined_developed",
    max_depth=3, n_estimators=100
)
```

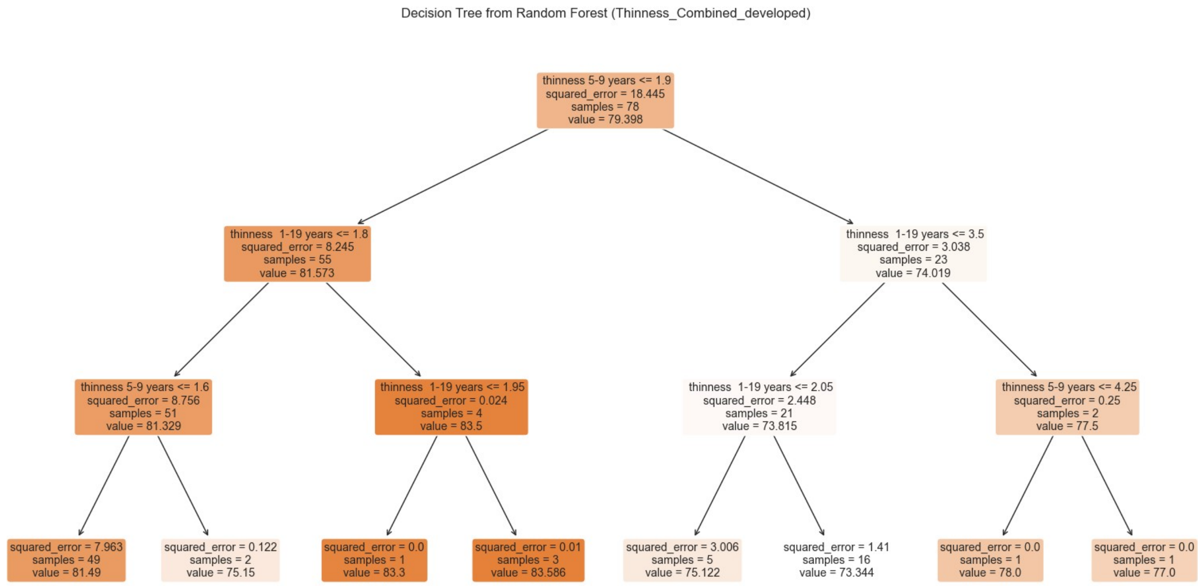
Decision Tree from Random Forest (Schooling_ICR_developed)



```
Train R² Score (Schooling_ICR_developed): 0.8141910279531419
Test R² Score (Schooling_ICR_developed): 0.7202442225695663
Train MSE (Schooling_ICR_developed): 3.409066523367135
Test MSE (Schooling_ICR_developed): 5.165255888966021
Train MAE (Schooling_ICR_developed): 1.3833220748114923
Test MAE (Schooling_ICR_developed): 1.6279531830352514
```




```
Train R² Score (Diphtheria_Polio_developed): 0.209895173153686
Test R² Score (Diphtheria_Polio_developed): -0.0008870547277304297
Train MSE (Diphtheria_Polio_developed): 14.496177905086808
Test MSE (Diphtheria_Polio_developed): 18.47982479971424
Train MAE (Diphtheria_Polio_developed): 2.920782346409489
Test MAE (Diphtheria_Polio_developed): 3.077530580771594
```

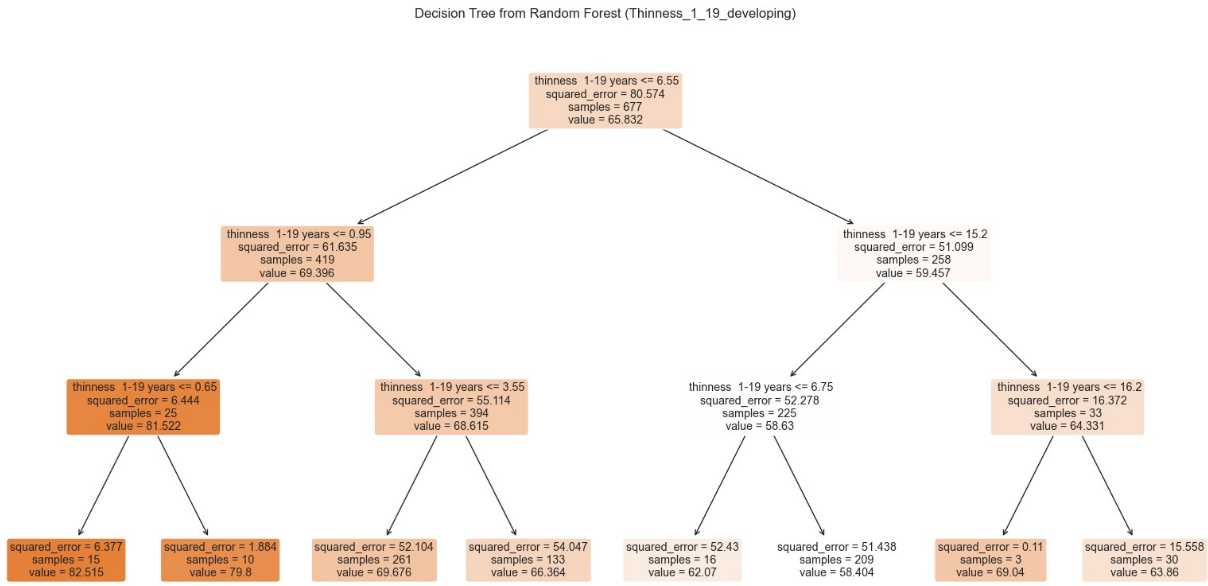



```
Train R² Score (Thinness_Combined_developed): 0.7304135308594408
Test R² Score (Thinness_Combined_developed): 0.5696531082452349
Train MSE (Thinness_Combined_developed): 4.946145479283211
Test MSE (Thinness_Combined_developed): 7.945686903596748
Train MAE (Thinness_Combined_developed): 1.667996142098984
Test MAE (Thinness_Combined_developed): 2.1039564879812156
```

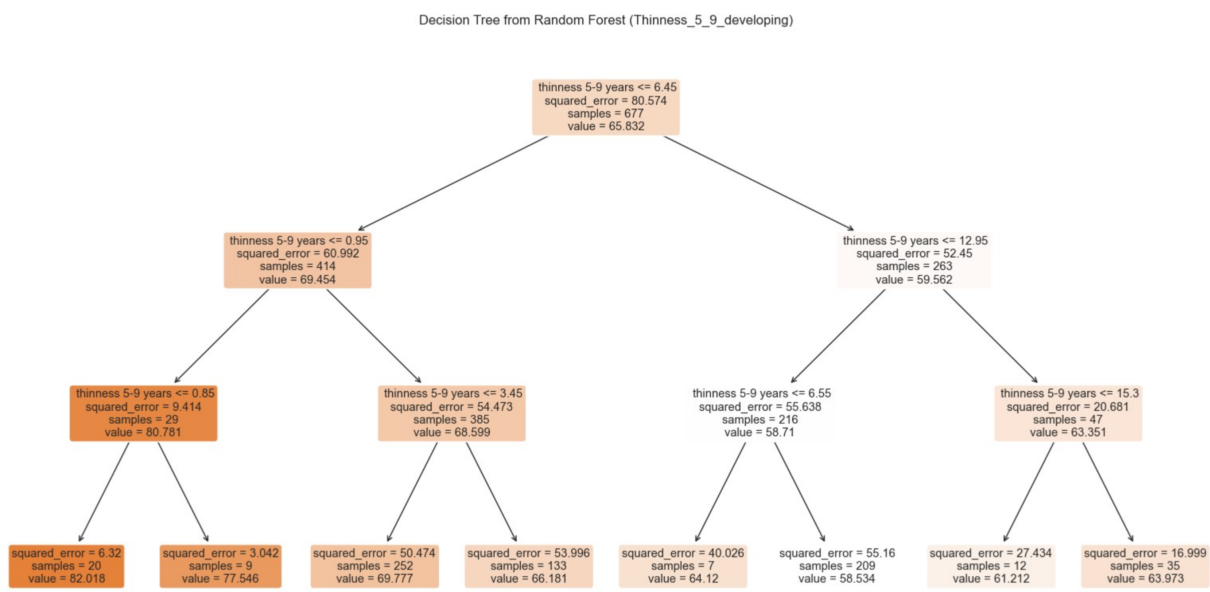
Random forest for developing

```python
# Evaluate Random Forest for Thinness_1_19_developing
evaluate_random_forest_regressor(
    Thinness_1_19_developing_train, Thinness_1_19_developing_test,
LE_developing_train, LE_developing_test,
    feature_name="Thinness_1_19_developing",
    max_depth=3, n_estimators=100
)

# Evaluate Random Forest for Thinness_5_9_developing
evaluate_random_forest_regressor(
    Thinness_5_9_developing_train, Thinness_5_9_developing_test,
LE_developing_train, LE_developing_test,
    feature_name="Thinness_5_9_developing",
    max_depth=3, n_estimators=100
)

# Adult Mortality
evaluate_random_forest_regressor(
    Adult_Mortality_developing_train, Adult_Mortality_developing_test,
    LE_developing_train, LE_developing_test,
    feature_name="Adult Mortality",
```

```
    max_depth=3, n_estimators=100
)

# Schooling
evaluate_random_forest_regressor(
    Schooling_developing_train, Schooling_developing_test,
    LE_developing_train, LE_developing_test,
    feature_name="Schooling",
    max_depth=3, n_estimators=100
)

# Income Composition of Resources (ICR)
evaluate_random_forest_regressor(
    ICR_developing_train, ICR_developing_test,
    LE_developing_train, LE_developing_test,
    feature_name="ICR",
    max_depth=3, n_estimators=100
)

# Diphtheria
evaluate_random_forest_regressor(
    Diphtheria_developing_train, Diphtheria_developing_test,
    LE_developing_train, LE_developing_test,
    feature_name="Diphtheria",
    max_depth=3, n_estimators=100
)

# Alcohol
evaluate_random_forest_regressor(
    Alcohol_developing_train, Alcohol_developing_test,
    LE_developing_train, LE_developing_test,
    feature_name="Alcohol",
    max_depth=3, n_estimators=100
)

# Polio
evaluate_random_forest_regressor(
    Polio_developing_train, Polio_developing_test,
LE_developing_train, LE_developing_test,
    feature_name="Polio",
    max_depth=3, n_estimators=100
)
```

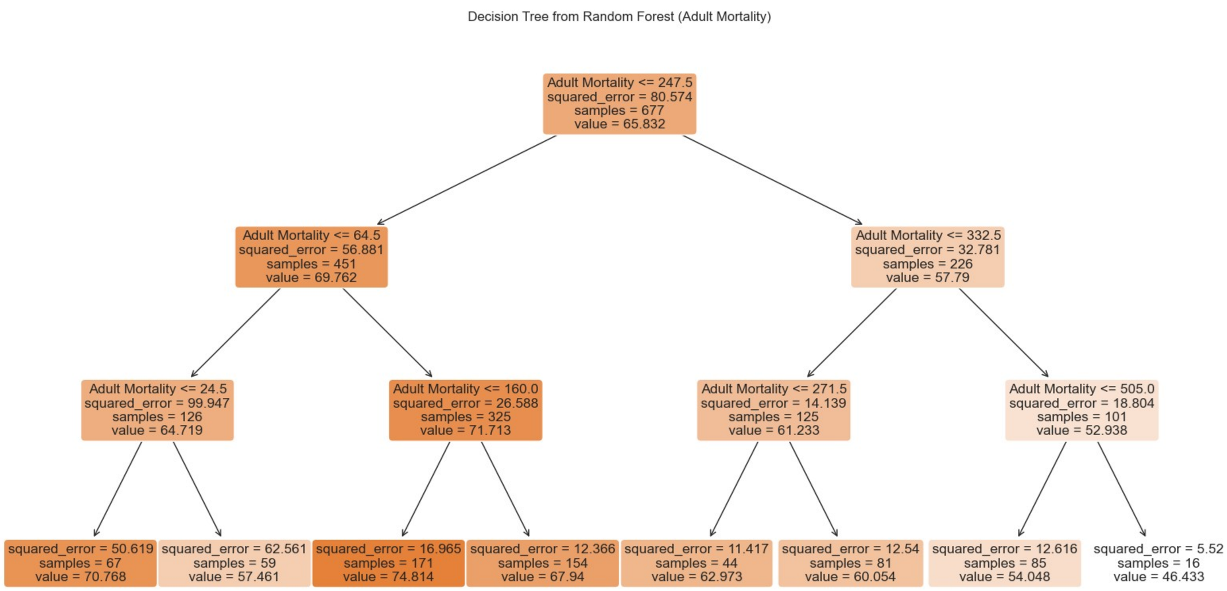



```
Train R² Score (Thinness_1_19_developing): 0.40579396898292874
Test R² Score (Thinness_1_19_developing): 0.4097116516124395
Train MSE (Thinness_1_19_developing): 49.87802160124323
Test MSE (Thinness_1_19_developing): 55.98768787528844
Train MAE (Thinness_1_19_developing): 5.479983701064628
Test MAE (Thinness_1_19_developing): 5.753684208743515
```

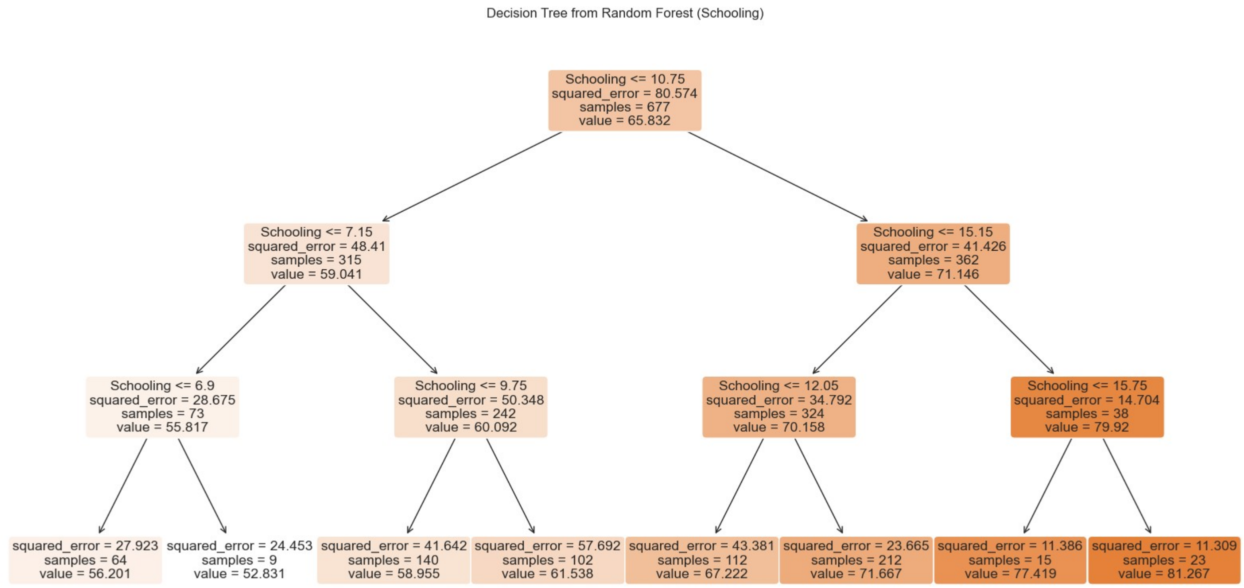



```
Train R² Score (Thinness_5_9_developing): 0.39974825682877
Test R² Score (Thinness_5_9_developing): 0.3878627821001345
Train MSE (Thinness_5_9_developing): 50.38550241712098
```

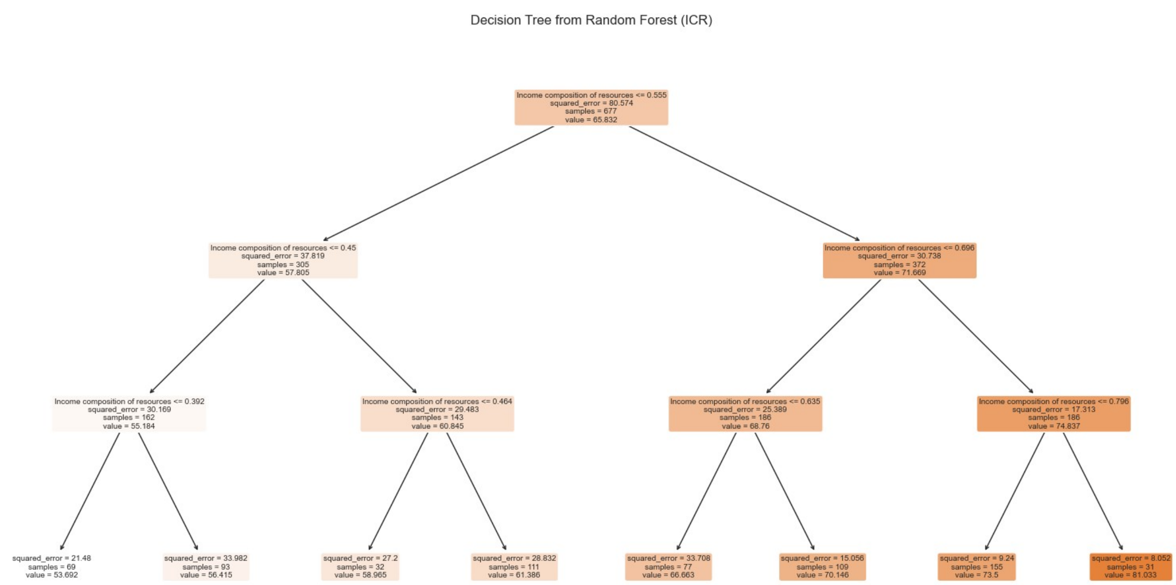
```
Test MSE (Thinness_5_9_developing): 58.06001013952478
Train MAE (Thinness_5_9_developing): 5.541023915455268
Test MAE (Thinness_5_9_developing): 5.835631049358315
```




```
Train R² Score (Adult Mortality): 0.7661541052345835
Test R² Score (Adult Mortality): 0.7396134751490426
Train MSE (Adult Mortality): 19.629168977816043
Test MSE (Adult Mortality): 24.697149317124587
Train MAE (Adult Mortality): 3.1158924072881726
Test MAE (Adult Mortality): 3.413024622706106
```

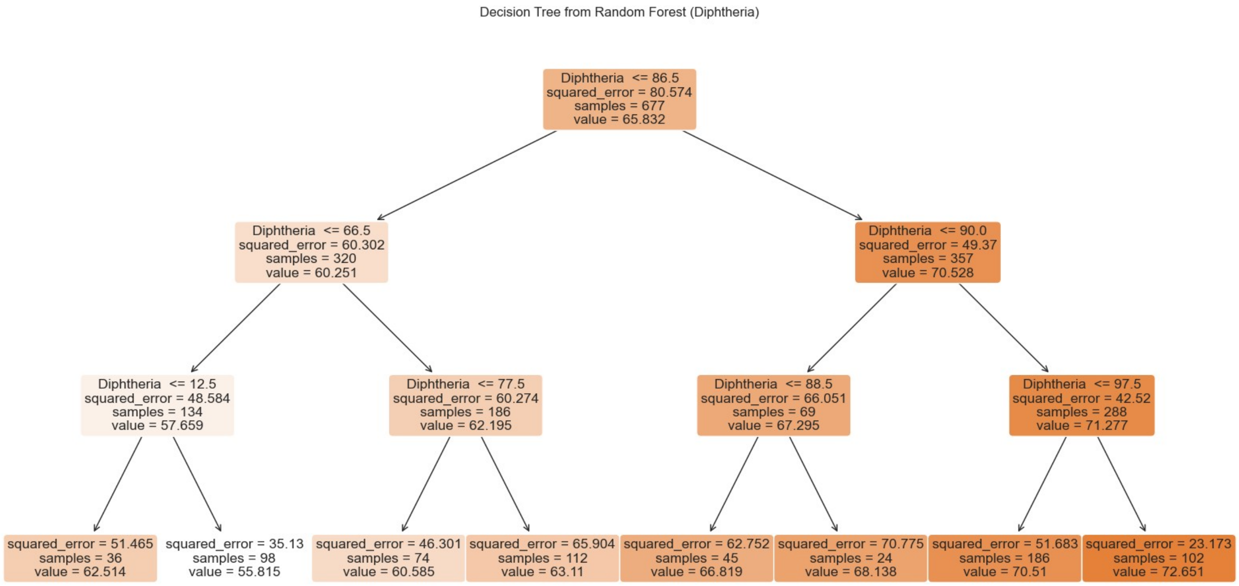



```
Train R² Score (Schooling): 0.5127713623339556
Test R² Score (Schooling): 0.5357046055121087
Train MSE (Schooling): 40.898273066422455
Test MSE (Schooling): 44.037504212186775
Train MAE (Schooling): 4.972248486186705
Test MAE (Schooling): 5.380311258045078
```

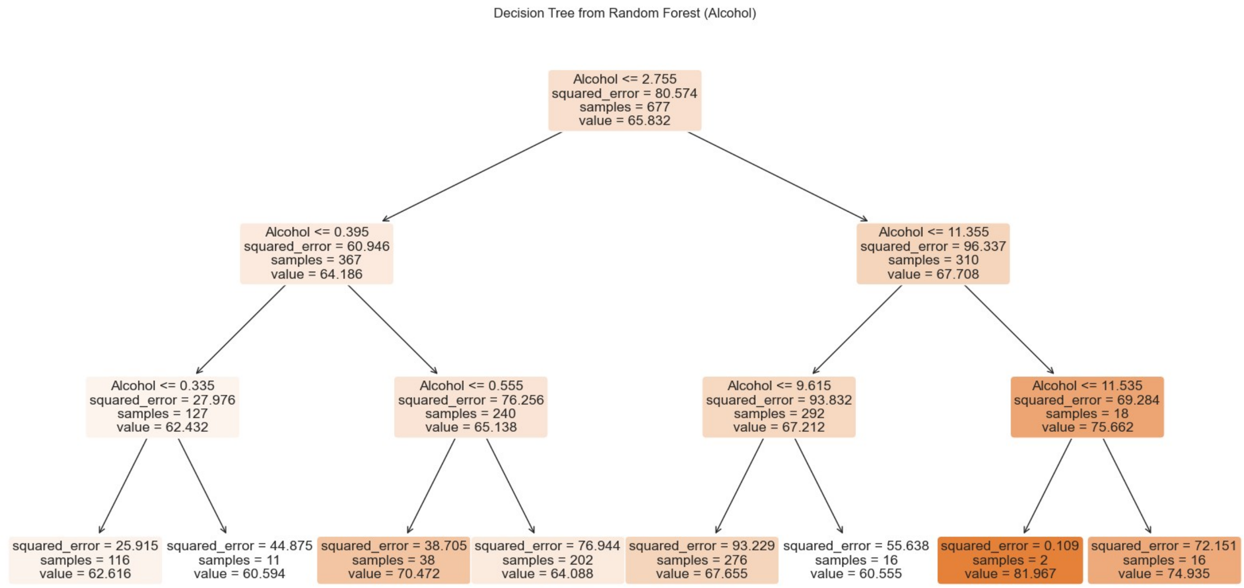



```
Train R² Score (ICR): 0.7220442778795755
Test R² Score (ICR): 0.7200778921005934
Train MSE (ICR): 23.331775156138384
```

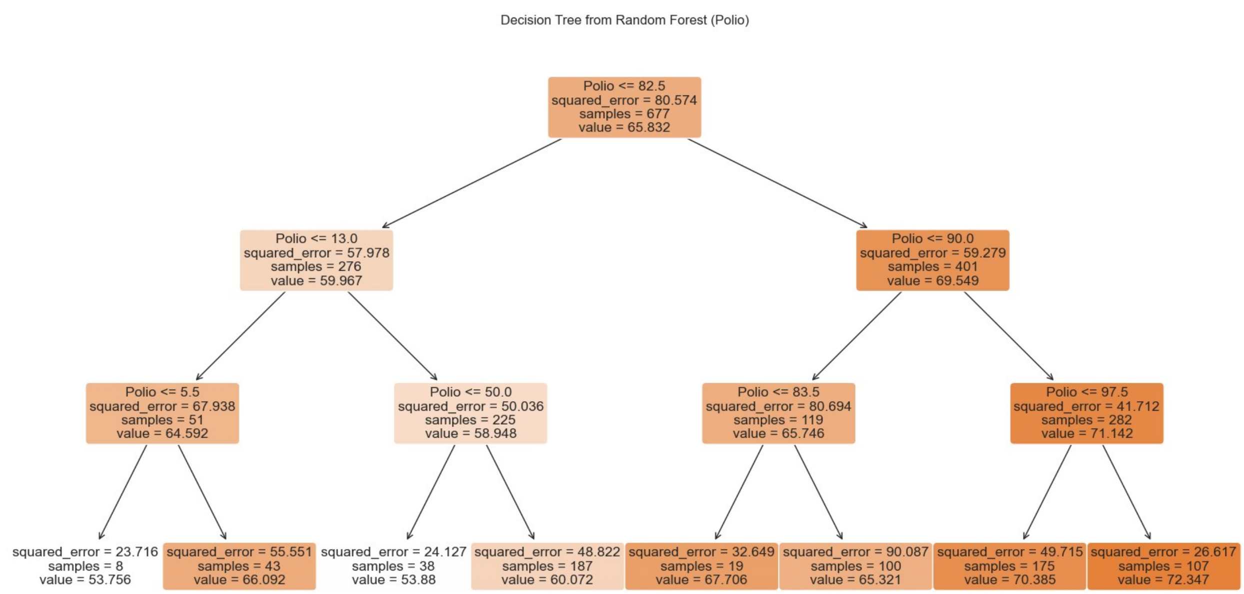
```
Test MSE (ICR): 26.550060913916322
Train MAE (ICR): 3.688644113205476
Test MAE (ICR): 3.980849002480152
```




```
Train R² Score (Diphtheria): 0.3521363543488245
Test R² Score (Diphtheria): 0.30939756064991664
Train MSE (Diphtheria): 54.38207494652835
Test MSE (Diphtheria): 65.50228193706303
Train MAE (Diphtheria): 5.8434851340778176
Test MAE (Diphtheria): 6.464627260944357
```




```
Train R² Score (Alcohol): 0.12365229557411428
Test R² Score (Alcohol): 0.041260440283986566
Train MSE (Alcohol): 73.56116809642153
Test MSE (Alcohol): 90.9345599819107
Train MAE (Alcohol): 7.106410556699105
Test MAE (Alcohol): 7.923567415415438
```

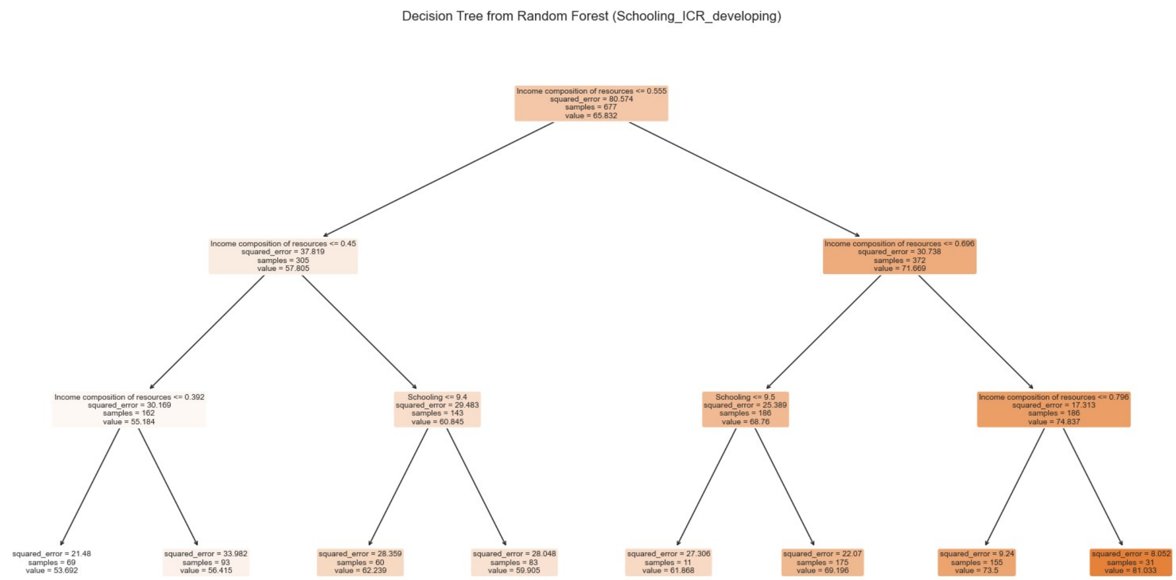



```
Train R² Score (Polio): 0.34754839852345276
Test R² Score (Polio): 0.30679359301429276
Train MSE (Polio): 54.76719079493492
```

```
Test MSE (Polio): 65.74926314145053
Train MAE (Polio): 5.818533452467429
Test MAE (Polio): 6.49900207126972
```

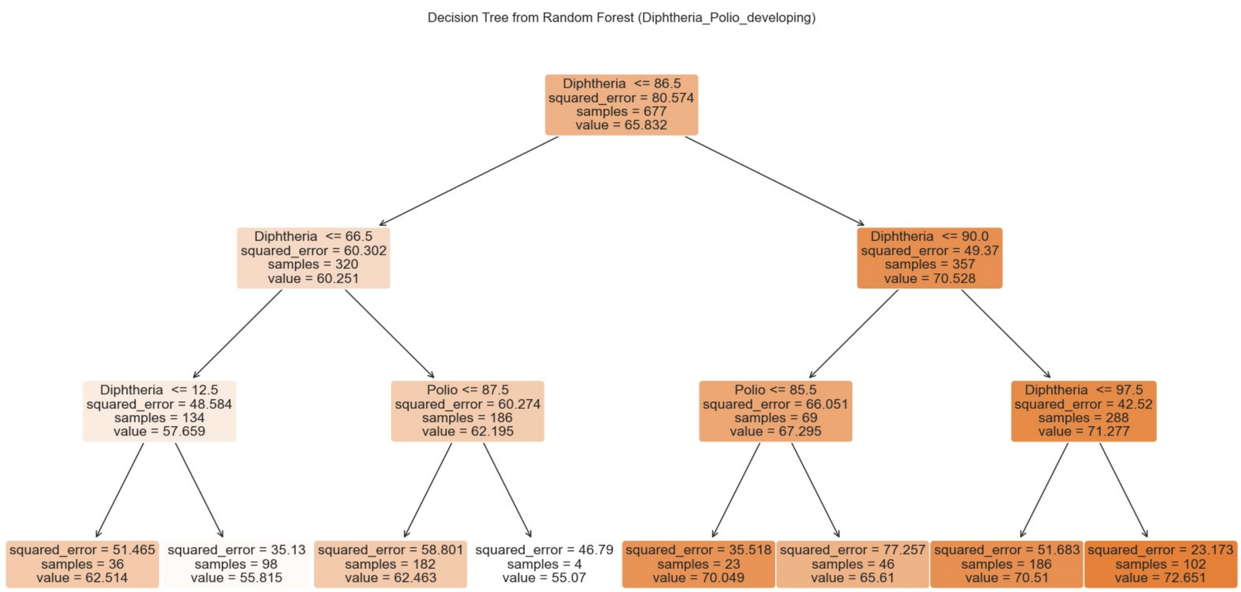
Random forest for developing multi-variates

```
evaluate_random_forest_regressor(
    Schooling_ICR_developing_train, Schooling_ICR_developing_test,
LE_developing_train, LE_developing_test,
    feature_name="Schooling_ICR_developing",
    max_depth=3, n_estimators=100
)
evaluate_random_forest_regressor(
    Diphtheria_Polio_developing_train,
Diphtheria_Polio_developing_test, LE_developing_train,
LE_developing_test,
    feature_name="Diphtheria_Polio_developing",
    max_depth=3, n_estimators=100
)
evaluate_random_forest_regressor(
    Thinness_Combined_developing_train,
Thinness_Combined_developing_test, LE_developing_train,
LE_developing_test,
    feature_name="Thinness_Combined_developing",
    max_depth=3, n_estimators=100
)
```

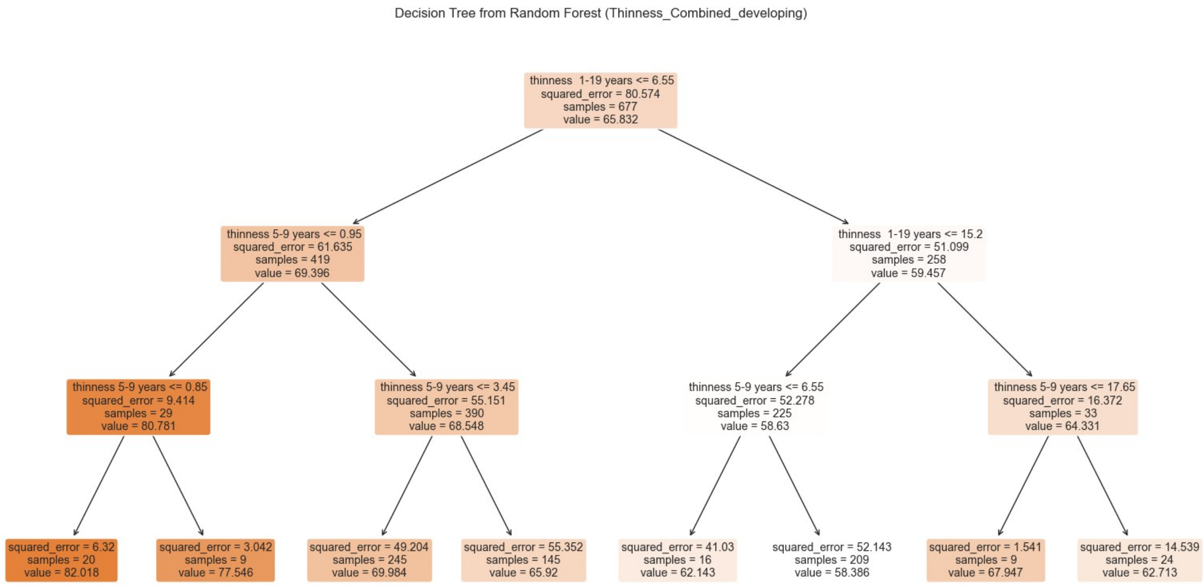



```
Train R² Score (Schooling_ICR_developing): 0.7352784401270449
Test R² Score (Schooling_ICR_developing): 0.7244625216479608
```

```
Train MSE (Schooling_ICR_developing): 22.220891395292345
Test MSE (Schooling_ICR_developing): 26.134187432392682
Train MAE (Schooling_ICR_developing): 3.598595299420881
Test MAE (Schooling_ICR_developing): 3.9255113917217743
```




```
Train R² Score (Diphtheria_Polio_developing): 0.36454814216380504
Test R² Score (Diphtheria_Polio_developing): 0.3149096151642493
Train MSE (Diphtheria_Polio_developing): 53.3402218039643
Test MSE (Diphtheria_Polio_developing): 64.97947441673331
Train MAE (Diphtheria_Polio_developing): 5.754489671990363
Test MAE (Diphtheria_Polio_developing): 6.425888235783003
```




```
Train R² Score (Thinness_Combined_developing): 0.41945492417870256
Test R² Score (Thinness_Combined_developing): 0.41304843719555295
Train MSE (Thinness_Combined_developing): 48.73131257645912
Test MSE (Thinness_Combined_developing): 55.67120033111713
Train MAE (Thinness_Combined_developing): 5.384367406771761
Test MAE (Thinness_Combined_developing): 5.646244652267137
```

In conclusion, for both developing and developed countries, the best indicators of life expectancy is actually socioeconomic factors, thinness and adult mortality. Specifically the best indicators is adult mortality, followed by income, schooling, thinness. To improve life expectancy we would have to target these few fronts.

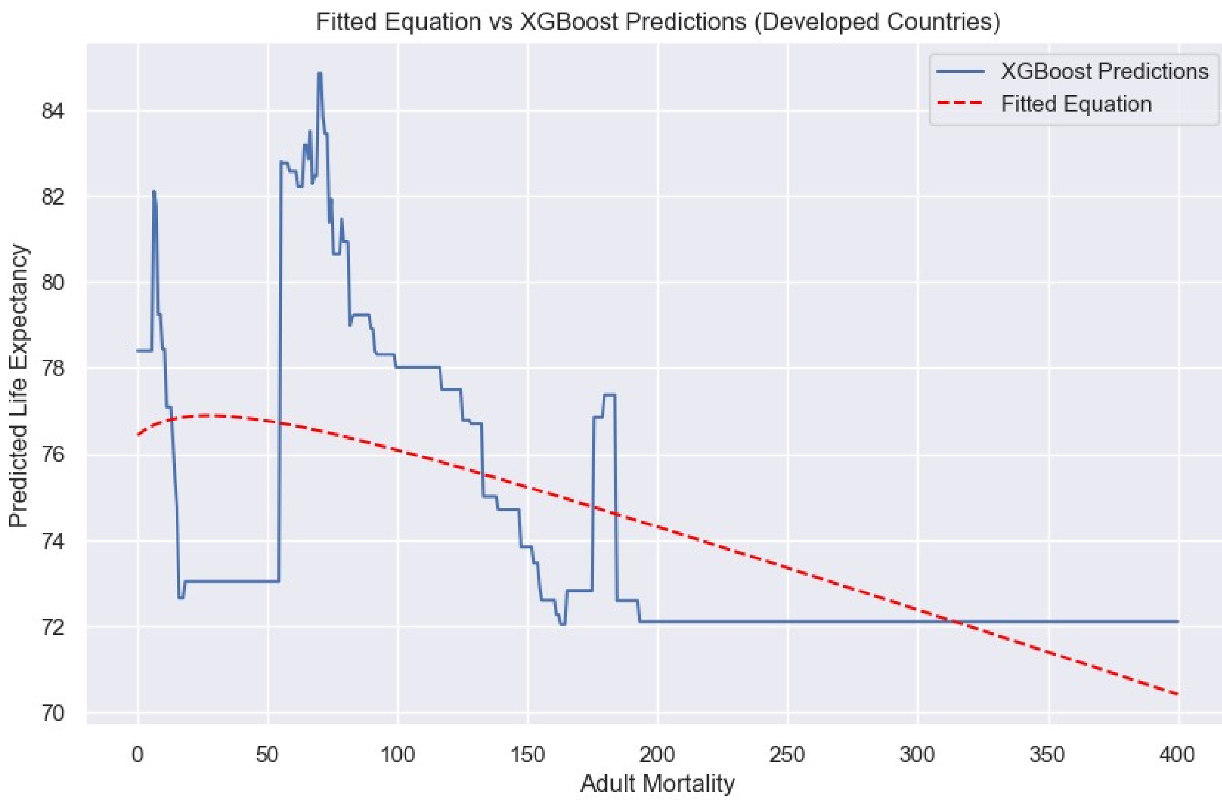
adult mortality, shift more healthcare resources to adults aged between 15-60

income, schooling, focus more on education that would eventually allow higher income and longer life expectancy

Thinness among youths, provide more education in schools on nutritious foods to reduce thinness as it may lead to long term health issues

```
from scipy.optimize import curve_fit
import numpy as np
import matplotlib.pyplot as plt
import xgboost as xgb

xgboost_model = xgb.XGBRegressor(max_depth=3, n_estimators=100,
learning_rate=0.1)
xgboost_model.fit(Adult_Mortality_developed_train, LE_developed_train)


x_vals = np.linspace(0, 400, 500).reshape(-1, 1)
y_preds = xgboost_model.predict(x_vals)

def rational_func(x, a, b, c, d):
    return (a * x**2 + b * x + c) / (x + d)

popt, _ = curve_fit(rational_func, x_vals.ravel(), y_preds)
a, b, c, d = popt


print(f"□ Approximated Equation for Developed Countries:")
print(f"Life Expectancy = ({a:.4f} * x² + {b:.4f} * x + {c:.4f}) / (x
+ {d:.4f})")


plt.figure(figsize=(10, 6))
```

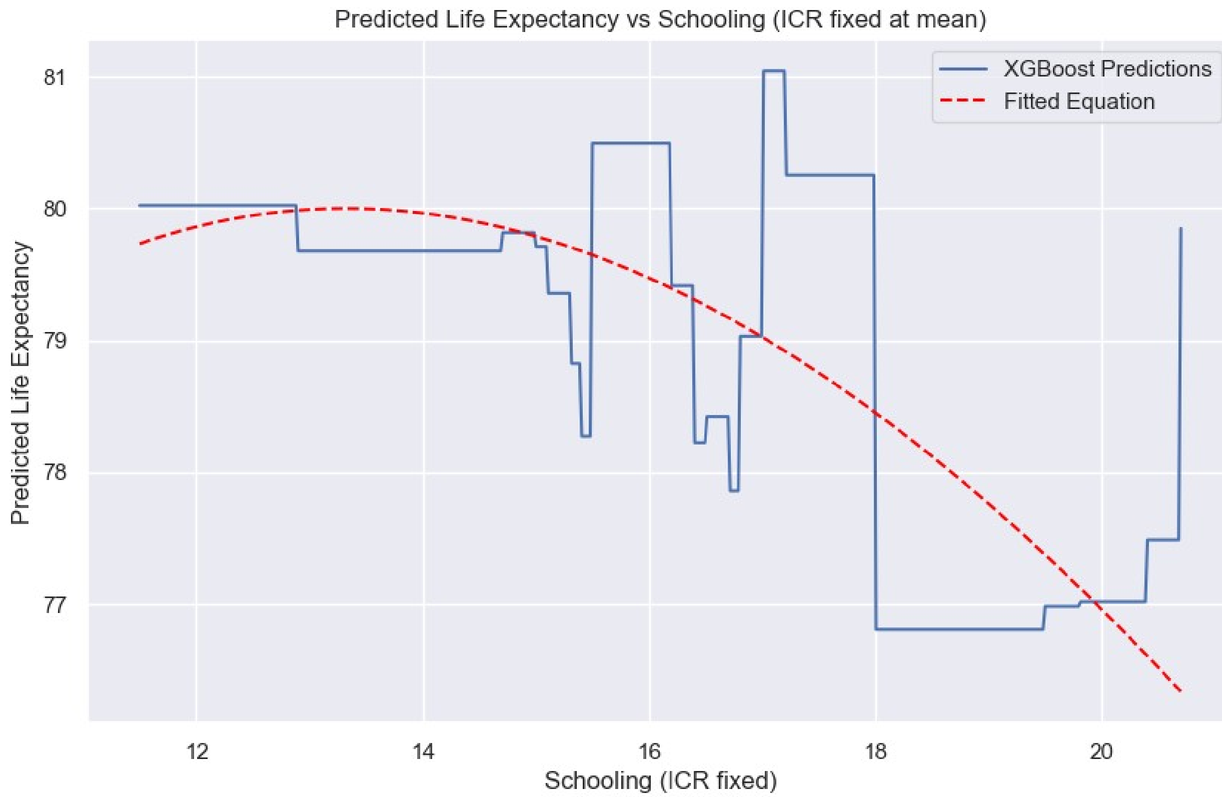
```
plt.plot(x_vals, y_preds, label="XGBoost Predictions")
plt.plot(x_vals, rational_func(x_vals.ravel(), *popt), '--',
label="Fitted Equation", color='red')
plt.xlabel("Adult Mortality")
plt.ylabel("Predicted Life Expectancy")
plt.title("Fitted Equation vs XGBoost Predictions (Developed
Countries)")
plt.legend()
plt.grid(True)
plt.show()

 Approximated Equation for Developed Countries:
Life Expectancy = (-0.0202 * x² + 77.9975 * x + 2483.0615) / (x +
32.4862)
```




```
from scipy.optimize import curve_fit
import numpy as np
import matplotlib.pyplot as plt
import xgboost as xgb

xgboost_model = xgb.XGBRegressor(max_depth=3, n_estimators=100,
learning_rate=0.1)
xgboost_model.fit(Schooling_ICR_developed_train, LE_developed_train)
```

```
min_val = Schooling_ICR_developed_train.iloc[:, 0].min()
max_val = Schooling_ICR_developed_train.iloc[:, 0].max()
icr_mean = Schooling_ICR_developed_train.iloc[:, 1].mean()


schooling_range = np.linspace(min_val, max_val, 500)
X_input = np.column_stack([schooling_range,
np.full_like(schooling_range, icr_mean)])


y_preds = xgboost_model.predict(X_input)


def rational_func(x, a, b, c, d):
    return (a * x**2 + b * x + c) / (x + d)

popt, _ = curve_fit(rational_func, schooling_range, y_preds)
a, b, c, d = popt


print(f"\n□ Approximated Equation (ICR fixed at {icr_mean:.2f}):")
print(f"Life Expectancy = ({a:.4f} * x² + {b:.4f} * x + {c:.4f}) / (x
+ {d:.4f})")


plt.figure(figsize=(10, 6))
plt.plot(schooling_range, y_preds, label="XGBoost Predictions")
plt.plot(schooling_range, rational_func(schooling_range, *popt), '--',
label="Fitted Equation", color='red')
plt.xlabel("Schooling (ICR fixed)")
plt.ylabel("Predicted Life Expectancy")
plt.title("Predicted Life Expectancy vs Schooling (ICR fixed at
mean)")
plt.legend()
plt.grid(True)
plt.show()
```

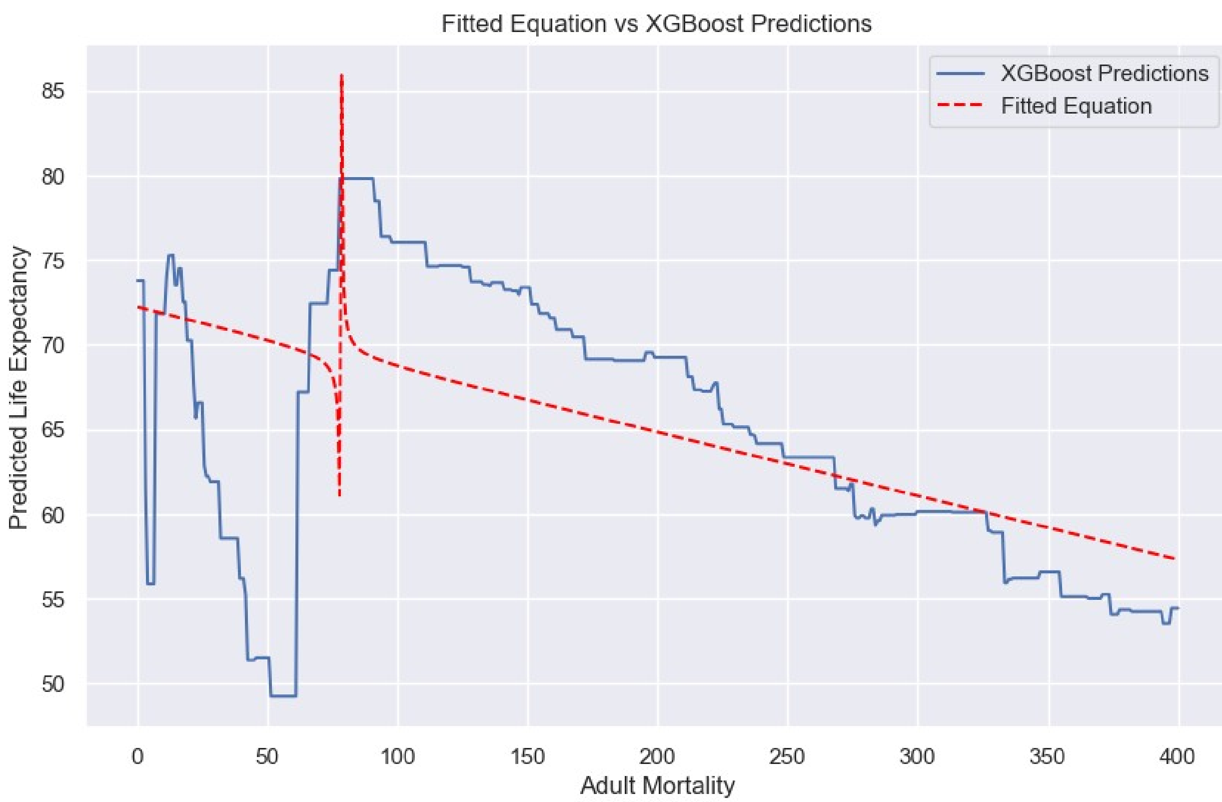
```
□ Approximated Equation (ICR fixed at 0.84):
Life Expectancy = (-3.7523 * x² + 179.9786 * x + 2137.2111) / (x +
35.0398)
```




```
from scipy.optimize import curve_fit


x_range = np.linspace(0, 400, 500).reshape(-1, 1)


xgboost_model = xgb.XGBRegressor(max_depth=3, n_estimators=100,
learning_rate=0.1)
xgboost_model.fit(Adult_Mortality_developing_train,
LE_developing_train)
y_preds = xgboost_model.predict(x_range)


def curve_func(x, a, b, c, d):
    return (a * x**2 + b * x + c) / (x + d)

popt, _ = curve_fit(curve_func, x_range.ravel(), y_preds)
a, b, c, d = popt


print(f"\n Approximated Equation (non-linear):")
print(f"Predicted Life Expectancy = ({a:.4f} * x² + {b:.4f} * x +
{c:.4f}) / (x + {d:.4f})")


plt.figure(figsize=(10, 6))
```

```
plt.plot(x_range, y_preds, label="XGBoost Predictions")
plt.plot(x_range, curve_func(x_range.ravel(), *popt), '--',
color='red', label="Fitted Equation")
plt.xlabel("Adult Mortality")
plt.ylabel("Predicted Life Expectancy")
plt.title("Fitted Equation vs XGBoost Predictions")
plt.legend()
plt.grid(True)
plt.show()
```

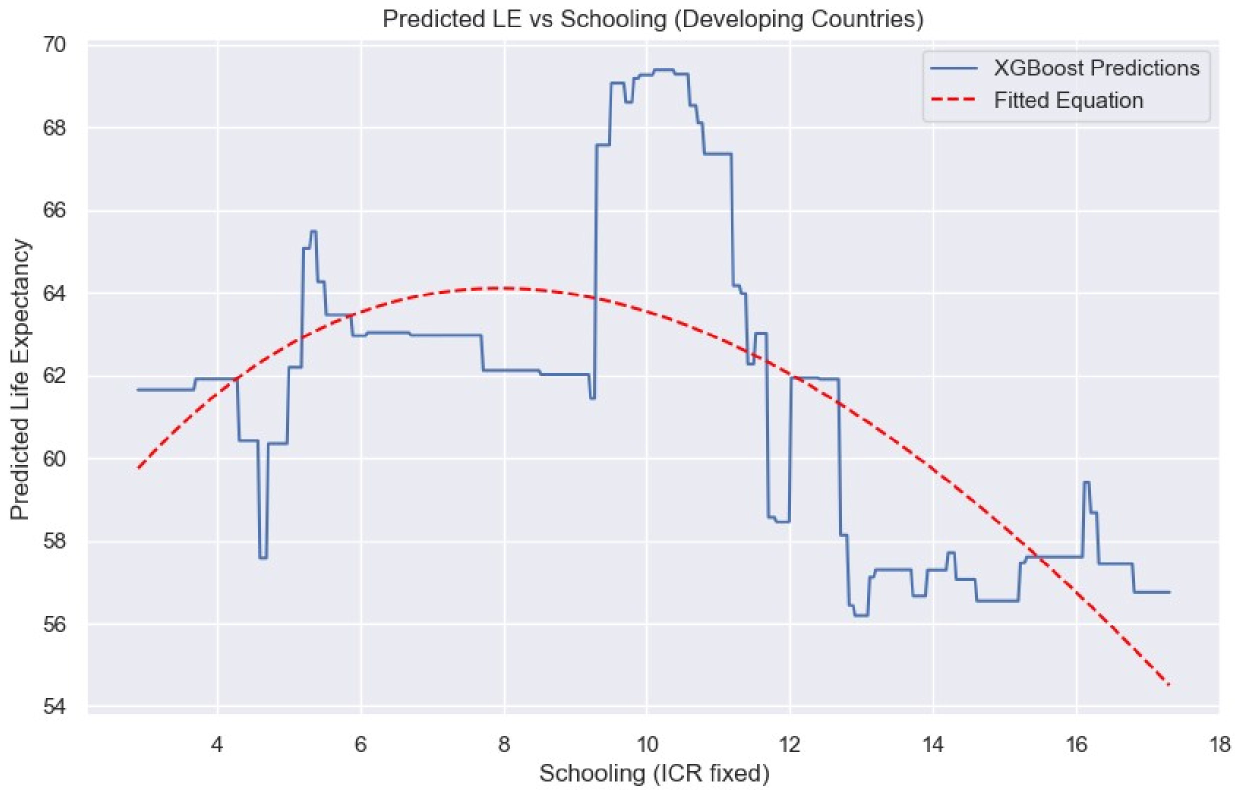
```
 Approximated Equation (non-linear):
Predicted Life Expectancy = (-0.0375 * x² + 75.2207 * x + -
5654.9617) / (x + -78.2901)
```




```
from scipy.optimize import curve_fit
import numpy as np
import matplotlib.pyplot as plt
import xgboost as xgb


xgboost_model = xgb.XGBRegressor(max_depth=3, n_estimators=100,
learning_rate=0.1)
xgboost_model.fit(Schooling_ICR_developing_train, LE_developing_train)
```

```
min_vals = Schooling_ICR_developing_train.min()
max_vals = Schooling_ICR_developing_train.max()

schooling_range = np.linspace(min_vals[0], max_vals[0], 500)
icr_mean = Schooling_ICR_developing_train.iloc[:, 1].mean()

X_input = np.column_stack([schooling_range,
np.full_like(schooling_range, icr_mean)])


y_preds = xgboost_model.predict(X_input)


def rational_func(x, a, b, c, d):
    return (a * x**2 + b * x + c) / (x + d)

popt, _ = curve_fit(rational_func, schooling_range, y_preds)
a, b, c, d = popt

print(f"\n Approximated Equation (ICR fixed at {icr_mean:.2f}):")
print(f"Life Expectancy = ({a:.4f} * x² + {b:.4f} * x + {c:.4f}) / (x
+ {d:.4f})")

plt.figure(figsize=(10, 6))
plt.plot(schooling_range, y_preds, label="XGBoost Predictions")
plt.plot(schooling_range, rational_func(schooling_range, *popt), '--',
color='red', label="Fitted Equation")
plt.xlabel("Schooling (ICR fixed)")
plt.ylabel("Predicted Life Expectancy")
plt.title("Predicted LE vs Schooling (Developing Countries)")
plt.legend()
plt.grid(True)
plt.show()
```

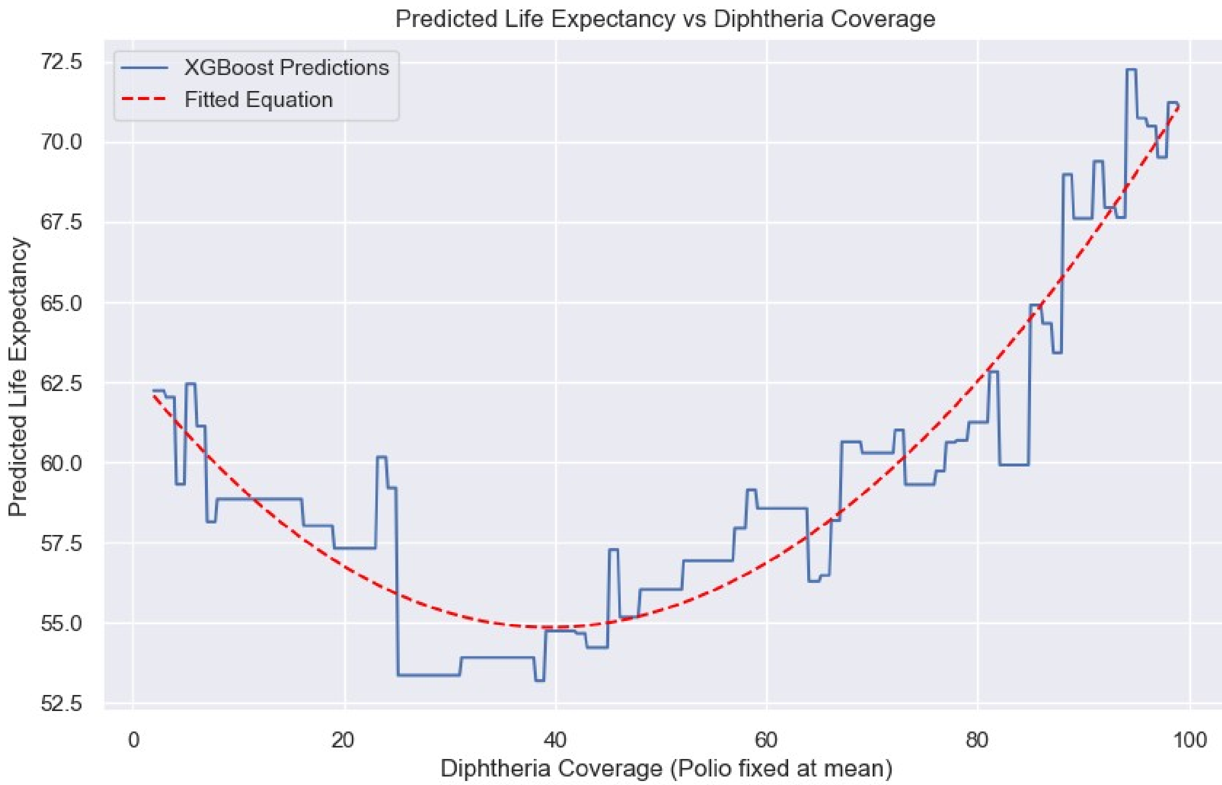
```
 Approximated Equation (ICR fixed at 0.58):
Life Expectancy = (-4.4326 * x² + 134.6008 * x + 1196.8634) / (x +
23.0437)

/var/folders/5j/frg2fp6n6kvg1t51v16fvjcm0000gn/T/
ipykernel_41942/2532113528.py:14: FutureWarning: Series.__getitem__
treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame
behavior). To access a value by position, use `ser.iloc[pos]`
  schooling_range = np.linspace(min_vals[0], max_vals[0], 500)
```




```
from scipy.optimize import curve_fit
import numpy as np
import matplotlib.pyplot as plt
import xgboost as xgb


xgboost_model = xgb.XGBRegressor(max_depth=3, n_estimators=100,
learning_rate=0.1)
xgboost_model.fit(Diphtheria_Polio_developing_train,
LE_developing_train)


min_vals = Diphtheria_Polio_developing_train.min()
max_vals = Diphtheria_Polio_developing_train.max()

diphtheria_range = np.linspace(min_vals.iloc[0], max_vals.iloc[0],
500)
polio_mean = Diphtheria_Polio_developing_train.iloc[:, 1].mean()


X_input = np.column_stack([diphtheria_range,
np.full_like(diphtheria_range, polio_mean)])


y_preds = xgboost_model.predict(X_input)
```

```
def rational_func(x, a, b, c, d):
    return (a * x**2 + b * x + c) / (x + d)

popt, _ = curve_fit(rational_func, diphtheria_range, y_preds)
a, b, c, d = popt


print(f"\n📈 Approximated Equation (Polio fixed at {polio_mean:.2f}):")
print(f"Life Expectancy = ({a:.4f} * x² + {b:.4f} * x + {c:.4f}) / (x
+ {d:.4f})")


plt.figure(figsize=(10, 6))
plt.plot(diphtheria_range, y_preds, label="XGBoost Predictions")
plt.plot(diphtheria_range, rational_func(diphtheria_range, *popt),
'--', color='red', label="Fitted Equation")
plt.xlabel("Diphtheria Coverage (Polio fixed at mean)")
plt.ylabel("Predicted Life Expectancy")
plt.title("Predicted Life Expectancy vs Diphtheria Coverage")
plt.legend()
plt.grid(True)
plt.show()
```

```
📈 Approximated Equation (Polio fixed at 76.62):
Life Expectancy = (4.1152 * x² + -270.2164 * x + 50264.8121) / (x +
799.3519)
```



Predicted Life Expectancy vs Diphtheria Coverage
XGBoost Predictions
Fitted Equation
Predicted Life Expectancy
Diphtheria Coverage (Polio fixed at mean)
72.5
70.0
67.5
65.0
62.5
60.0
57.5
55.0
52.5
0
20
40
60
80
100