Clustering the Countries for HELP International

Objective:

To categorise the countries using socio-economic and health factors that determine the overall development of the country.

About organization:

HELP International is an international humanitarian NGO that is committed to fighting poverty and providing the people of backward countries with basic amenities and relief during the time of disasters and natural calamities.

Problem Statement

HELP International have been able to raise around $ 10 million. Now the CEO of the NGO needs to decide how to use this money strategically and effectively. So, CEO has to make decision to choose the countries that are in the direst need of aid. Hence, your Job as a Data scientist is to categorise the countries using some socio-economic and health factors that determine the overall development of the country. Then you need to suggest the countries which the CEO needs to focus on the most.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import warnings

warnings.filterwarnings('ignore')
plt.style.use('ggplot')
pd.set_option('display.max_colwidth', 250)
```

```
C:\Users\Omar\anaconda3\lib\site-packages\scipy\__init__.py:155: UserWarning: A NumPy ve
rsion >=1.18.5 and <1.25.0 is required for this version of SciPy (detected version 1.26.
0
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [2]:

```
df = pd.read_csv("data/countries/Country-data.csv")
df.head()
```

Out[2]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

In [3]:
```
df.shape
```
Out[3]:
```
(167, 10)
```

Explain The Features

In [4]:
```
exp = pd.read_csv("data/countries/data-dictionary.csv")
exp
```
Out[4]:

	Column Name	Description
0	country	Name of the country
1	child_mort	Death of children under 5 years of age per 1000 live births
2	exports	Exports of goods and services per capita. Given as %age of the GDP per capita
3	health	Total health spending per capita. Given as %age of GDP per capita
4	imports	Imports of goods and services per capita. Given as %age of the GDP per capita
5	Income	Net income per person
6	Inflation	The measurement of the annual growth rate of the Total GDP
7	life_expec	The average number of years a new born child would live if the current mortality patterns are to remain the same
8	total_fer	The number of children that would be born to each woman if the current age-fertility rates remain the same.
9	gdpp	The GDP per capita. Calculated as the Total GDP divided by the total population.

Describe The Data

In [5]:
```
df.describe()
```
Out[5]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	
mean	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689	2.947964	12
std	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172	1.513848	18
min	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000	1.150000	
25%	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000	1.795000	1
50%	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000	2.410000	4
75%	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000	3.880000	14
max	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000	7.490000	105

- **The minimum of child death rate is 2.6 and the maximum is 208. The average is 38.27**
- **The inflation has negative values which means bad economic stability**
- **The average number of children per each woman is approximately 3.0 children**
- **The highest GDPP is 105000, and the lowest is 231 and the average is 12964**

In [6]:
```
df[df["gdpp"]==231]
```

Out[6]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
26	Burundi	93.6	8.92	11.6	39.2	764	12.3	57.7	6.26	231

The country with the lowest gdpp is Burundi (An african country)

In [7]:
```
df[df["gdpp"]==105000]
```

Out[7]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
91	Luxembourg	2.8	175.0	7.77	142.0	91700	3.62	81.3	1.63	105000

The country with the lowest gdpp is Luxembourg (An European country)

In [8]:
```
df[(df["gdpp"]<13000) & (df["gdpp"]>12500)]
```

Out[8]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
33	Chile	8.7	37.7	7.96	31.3	19400	8.96	79.1	1.88	12900
121	Poland	6.0	40.1	7.46	42.1	21800	1.66	76.3	1.41	12600

The countries with the average gdpp are countries like Chile and Poland

In [9]:
```
df[(df["inflation"]>=0) & (df["inflation"]<=3)].head()
```

Out[9]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.440	76.8	2.13	12200
7	Australia	4.8	19.8	8.73	20.9	41400	1.160	82.0	1.93	51900
8	Austria	4.3	51.3	11.00	47.8	43200	0.873	80.5	1.44	46900
13	Barbados	14.2	39.5	7.97	48.7	15300	0.321	76.7	1.78	16000
15	Belgium	4.5	76.4	10.70	74.7	41100	1.880	80.0	1.86	44400

Central banks and economists often target a specific inflation rate to maintain price stability while promoting economic growth. While opinions on what constitutes a "good" inflation rate can vary, many central banks aim for an inflation target around 2% annually

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 167 entries, 0 to 166
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   country     167 non-null    object 
 1   child_mort  167 non-null    float64
 2   exports     167 non-null    float64
 3   health      167 non-null    float64
 4   imports     167 non-null    float64
 5   income      167 non-null    int64  
 6   inflation   167 non-null    float64
 7   life_expec  167 non-null    float64
 8   total_fer   167 non-null    float64
 9   gdpp        167 non-null    int64  
dtypes: float64(7), int64(2), object(1)
memory usage: 13.2+ KB
```

In [11]:
```
df[df.duplicated()]
```

Out[11]:

country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp

Columns Renaming

In [12]:
```
df = df.rename(columns={"total_fer":"children_per_woman"})
df.head()
```

Out[12]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	children_per_woman	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

First, Financial aid (What countries deserve financial aid the most ?)

In [13]:
```
X = df[["child_mort", "life_expec", "income", "gdpp"]]
X.head()
```

Out[13]:

	child_mort	life_expec	income	gdpp
0	90.2	56.2	1610	553
1	16.6	76.3	9930	4090
2	27.3	76.5	12900	4460
3	119.0	60.1	5900	3530
4	10.3	76.8	19100	12200

Data Visualization - Features Understanding

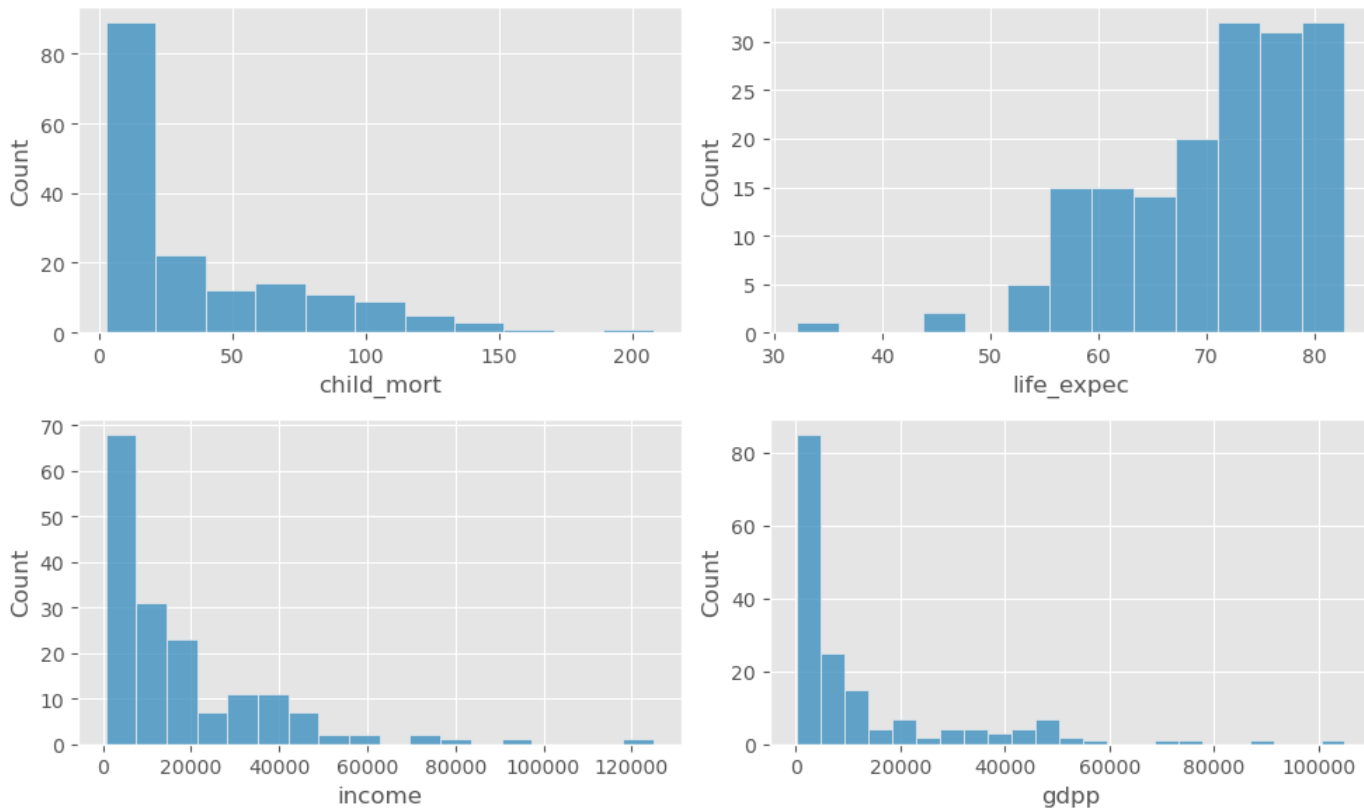
In [14]:
```
def draw_hist():
    fig = plt.figure(figsize=(10,6))
    for i in range(len(X.columns)):
        plt.subplot(2,2,i+1)
        sns.histplot(X[X.columns[i]], bins='auto')
        plt.tight_layout()
    plt.show()

def draw_box():
    fig = plt.figure(figsize=(10,6))
    for i in range(len(X.columns)):
        plt.subplot(2,2,i+1)
        sns.boxplot(X[X.columns[i]])
        plt.tight_layout()
    plt.show()
```

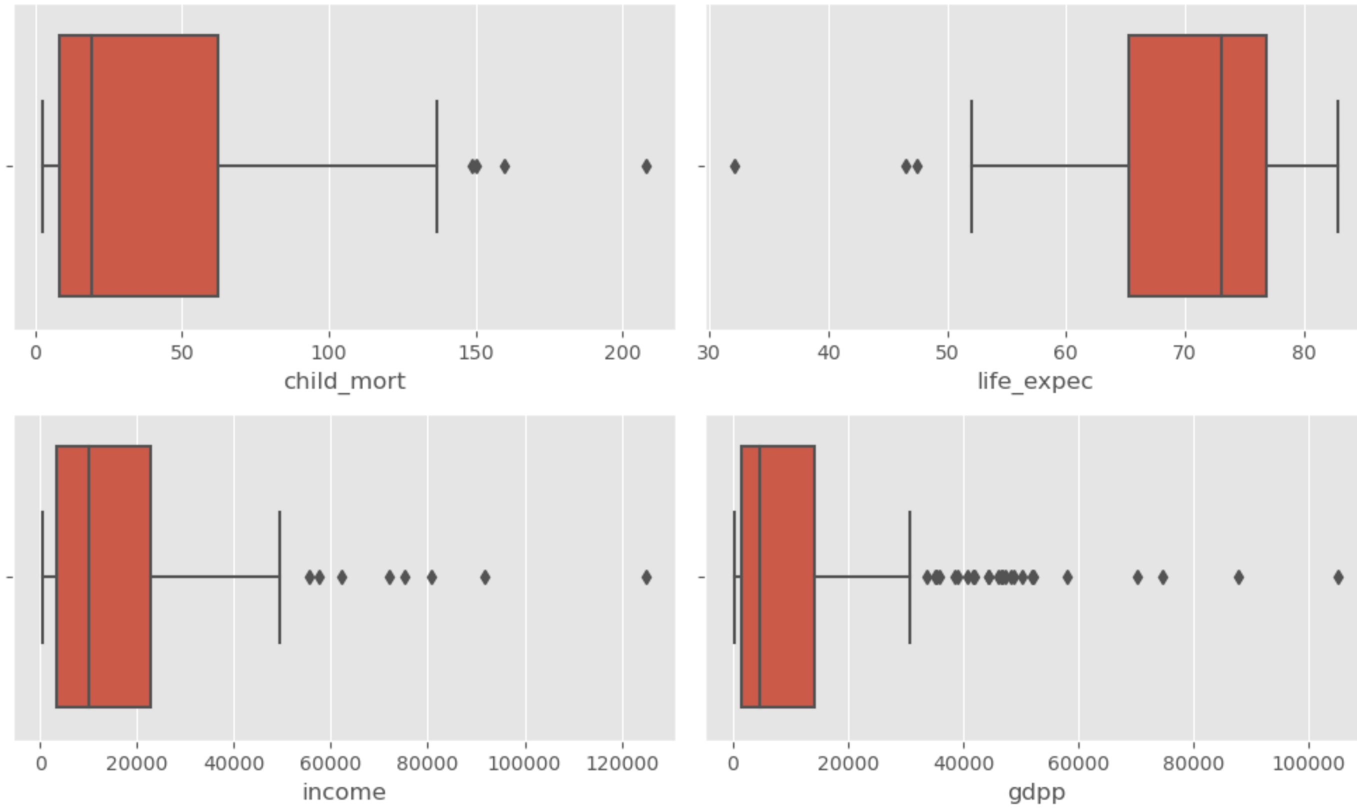
```python
def remove_outliers():
    for i in X.columns:
        Q3 = np.percentile(X[i], 75)
        Q1= np.percentile(X[i], 25)
        IQR = Q3 - Q1
        Max_Val = Q3 + (1.5*IQR)
        Min_Val = Q1 - (1.5*IQR)
        X.drop(X[X[i] > Max_Val].index, inplace=True)
        X.drop(X[X[i] < Min_Val].index, inplace=True)

def impute_outliers_with_median():
    for i in X.columns:
        Q3 = np.percentile(X[i], 75)
        Q1= np.percentile(X[i], 25)
        IQR = Q3 - Q1
        Max_Val = Q3 + (1.5*IQR)
        Min_Val = Q1 - (1.5*IQR)
        X.loc[X[i] > Max_Val, i] = X[i].median()
        X.loc[X[i] < Min_Val, i] = X[i].median()
```

In [15]:
```python
draw_hist()
```



In [16]:
```python
draw_box()
```



Handling Outliers

We shouldn't remove outliers becuase the nature of this data it is normal to have etreme or different data than usual

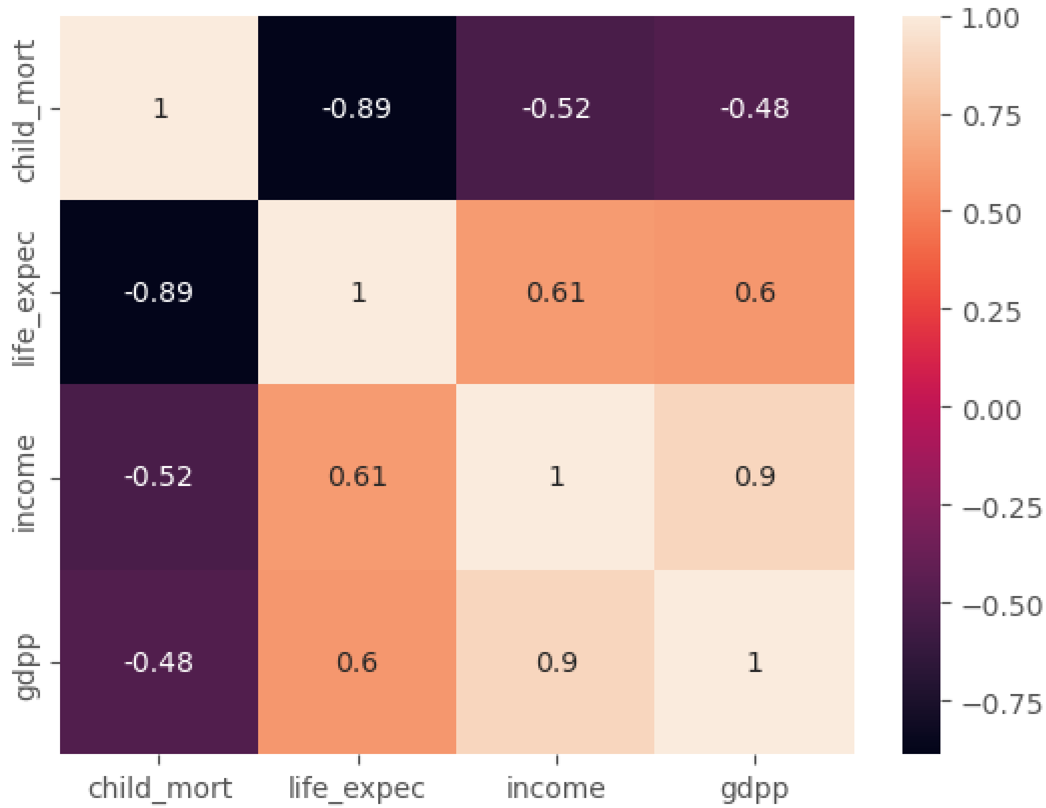
In [17]:
```
X.shape
```

Out[17]:
```
(167, 4)
```

See correlation between features

Heat Map

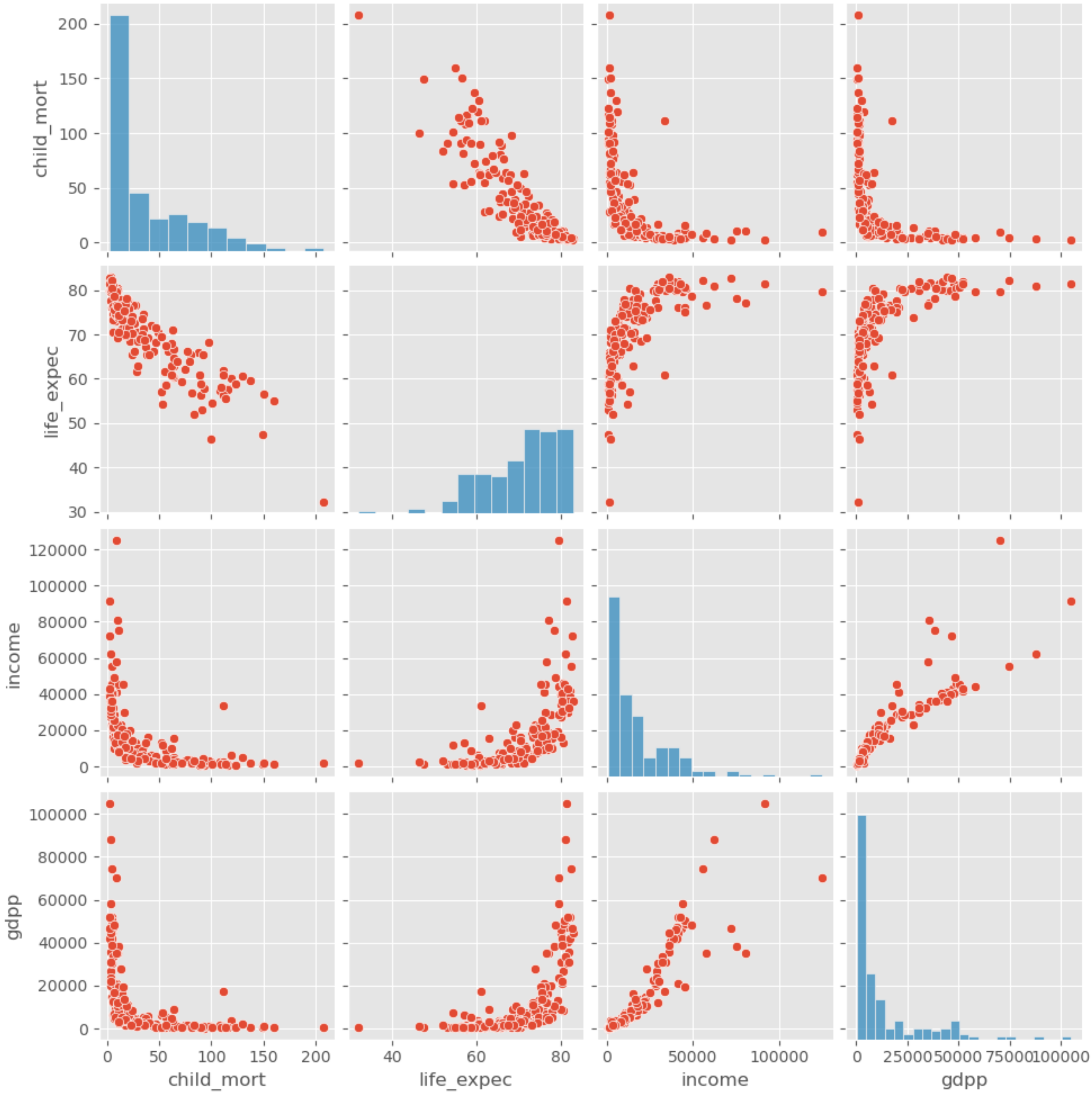
In [18]:
```
correlation = X.corr()
sns.heatmap(correlation, annot=True)
plt.show()
```



- ***There is a high correlation between features***
- ***There is a high positive correlation between income per person and GDP per capita***
- ***There is a high negative correlation between the birth life expectation (life_expec) and rate of children death (child_mort).***
- ***There is a negative correlation between rate of death of children under 5 and income per person. This means that in countries that income per person is higher, the children death rate is lower.***
- ***There is a negative correlation between rate of death of children under 5 and GDPP. This means that countries with higher GDPP have lower children death rate. And this indicates a better healthcare in countries with higher economical growth.***

Pairplot

In [19]:
```
sns.pairplot(X)
plt.show()
```



Observations:

1. The relation between income and gdpp has positive correlation.
2. The relation between life_expec and child_mort is approximately **linear** and have negative correlation.
3. The relation between other features are **not linear**.

In [20]:

```
X.head()
```

Out[20]:

	child_mort	life_expec	income	gdpp
0	90.2	56.2	1610	553
1	16.6	76.3	9930	4090
2	27.3	76.5	12900	4460
3	119.0	60.1	5900	3530
4	10.3	76.8	19100	12200

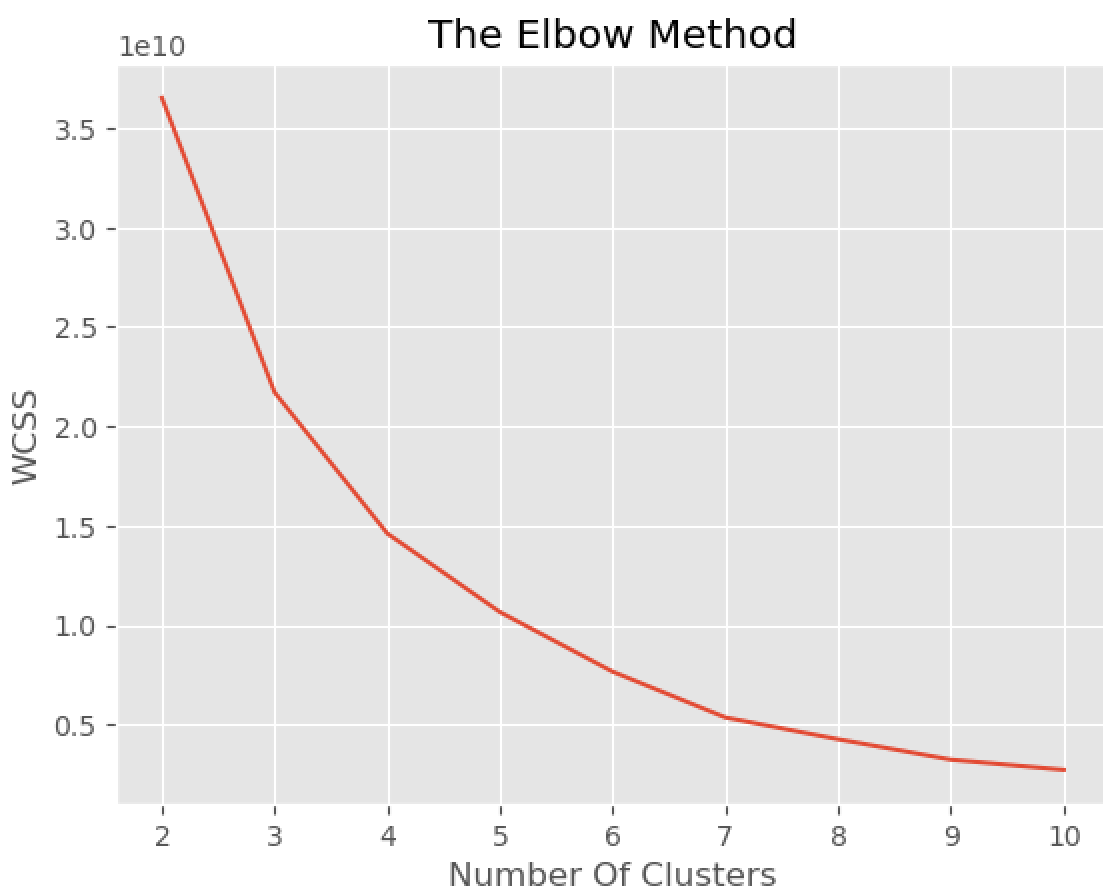
Choosing The Number Of Clusters - The Elbow Method

In [21]:

```
from sklearn.cluster import KMeans

WCSS = []
for i in range(2,11):
    kmeans = KMeans(n_clusters=i, init='k-means++')
    kmeans.fit(X)
    WCSS.append(kmeans.inertia_)

plt.plot(range(2,11), WCSS)
plt.title("The Elbow Method")
plt.xlabel("Number Of Clusters")
plt.ylabel("WCSS")
plt.show()
```



Make Clusters - The Model

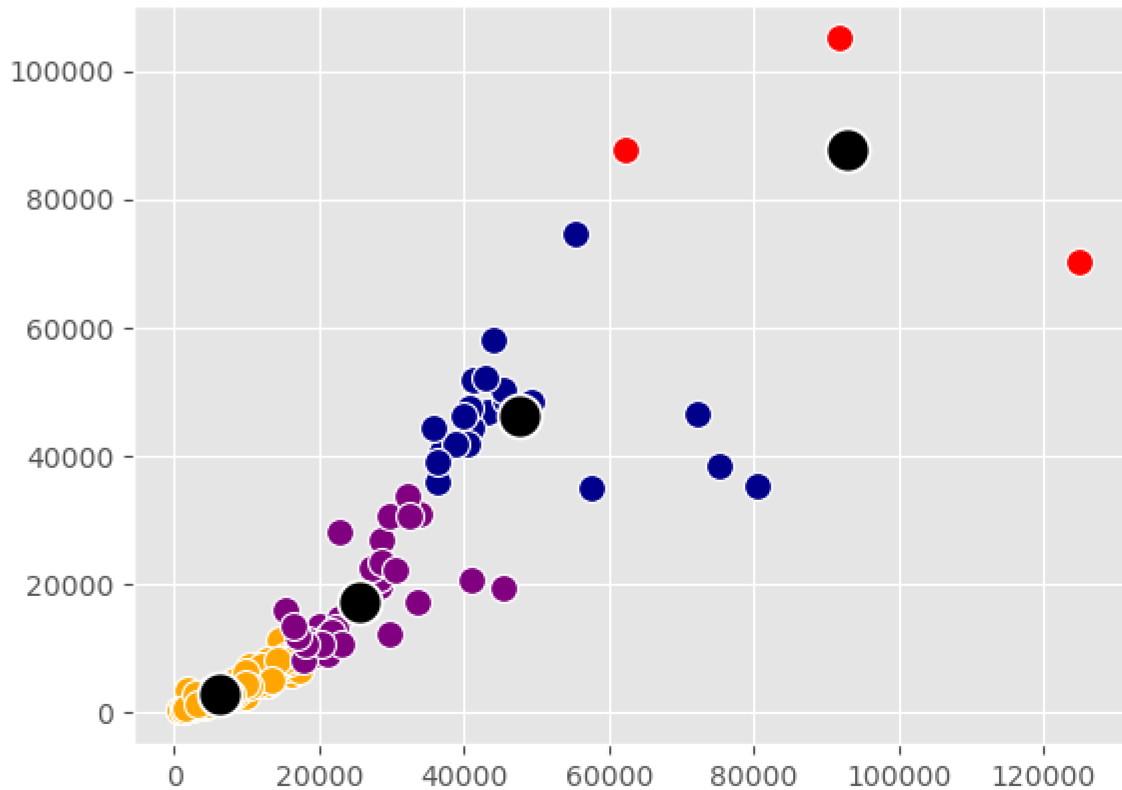
In [22]:

```
kmeans = KMeans(n_clusters=4, init='k-means++')
y_kmeans = kmeans.fit_predict(X)
```

In [23]:
```
XV = X.values
```

Visualizing Clusters

In [24]:
```
sns.scatterplot(XV[y_kmeans==0, 2], XV[y_kmeans==0, 3], s=100, color="darkblue")
sns.scatterplot(XV[y_kmeans==1, 2], XV[y_kmeans==1, 3], s=100, color="orange")
sns.scatterplot(XV[y_kmeans==2, 2], XV[y_kmeans==2, 3], s=100, color="purple")
sns.scatterplot(XV[y_kmeans==3, 2], XV[y_kmeans==3, 3], s=100, color="red")
sns.scatterplot(kmeans.cluster_centers_[:,2], kmeans.cluster_centers_[:,3], color="black
plt.show()
```



1. Orange => The poor countries => C1
2. Purple => The normal/good countries => C2
3. Blue => The very good Countries (rich) => C0
4. Red => he rich countries (very rich - extreme) => C3

Understand The Results

First Cluster

In [25]:
```
X[y_kmeans==1].describe()
```

Loading [MathJax]/extensions/Safe.js

Out[25]:

	child_mort	life_expec	income	gdpp
count	108.000000	108.000000	108.000000	108.000000
mean	54.135185	66.566667	6381.138889	3027.259259
std	41.160845	8.289392	4755.616179	2499.752000
min	5.500000	32.100000	609.000000	231.000000
25%	19.600000	60.650000	2065.000000	856.500000
50%	41.350000	68.050000	5295.000000	2695.000000
75%	80.475000	73.325000	9922.500000	4545.000000
max	208.000000	80.400000	17400.000000	11200.000000

- The average gdpp = 3027
- The minimum gdpp = 231, which is very low
- The maximum gdpp = 11200, which is normal but we can say **"not bad"** instead of **"good"**
- The income data is per year, which are very low
- The child_mort is very high, which means bad life quality

See data of first cluster - Poor Countries

In [27]:

```
data_index = X[y_kmeans==1].index
Cluster1 = df.loc[data_index]
Cluster1.head()
```

Out[27]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	children_per_woman	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
6	Armenia	18.1	20.8	4.40	45.3	6700	7.77	73.3	1.69	3220

Second Cluster

In [28]:

```
X[y_kmeans==2].describe()
```

Out[28]:

	child_mort	life_expec	income	gdpp
count	35.000000	35.000000	35.000000	35.000000
mean	12.102857	76.062857	25600.000000	17347.714286
std	17.918861	4.107746	7813.261728	7238.888071
min	3.200000	60.900000	15300.000000	8230.000000
25%	5.050000	74.500000	19750.000000	11950.000000
50%	7.900000	76.100000	22900.000000	14600.000000
75%	14.000000	79.300000	29600.000000	21600.000000
max	111.000000	81.900000	45400.000000	33700.000000

In [29]:
```
data_index = X[y_kmeans==2].index
Cluster2 = df.loc[data_index]
Cluster2.head()
```

Out[29]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	children_per_woman	gdpp
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.440	76.8	2.13	12200
5	Argentina	14.5	18.9	8.10	16.0	18700	20.900	75.8	2.37	10300
10	Bahamas	13.8	35.0	7.89	43.7	22900	-0.393	73.8	1.86	28000
11	Bahrain	8.6	69.5	4.97	50.9	41100	7.440	76.0	2.16	20700
13	Barbados	14.2	39.5	7.97	48.7	15300	0.321	76.7	1.78	16000

Third Cluster

In [30]:
```
X[y_kmeans==0].describe()
```

Out[30]:

	child_mort	life_expec	income	gdpp
count	21.000000	21.000000	21.000000	21.000000
mean	5.042857	80.457143	47571.428571	46085.714286
std	2.338284	1.720631	13249.797842	8897.038030
min	2.600000	76.500000	35800.000000	35000.000000
25%	4.000000	80.000000	39800.000000	40600.000000
50%	4.300000	80.500000	42900.000000	46200.000000
75%	5.200000	81.700000	49400.000000	48700.000000
max	10.800000	82.800000	80600.000000	74600.000000

In [31]:
```
data_index = X[y_kmeans==0].index
Cluster3 = df.loc[data_index]
Cluster3.head()
```

Out[31]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	children_per_woman	gdpp
7	Australia	4.8	19.8	8.73	20.9	41400	1.160	82.0	1.93	51900
8	Austria	4.3	51.3	11.00	47.8	43200	0.873	80.5	1.44	46900
15	Belgium	4.5	76.4	10.70	74.7	41100	1.880	80.0	1.86	44400
23	Brunei	10.5	67.4	2.84	28.0	80600	16.700	77.1	1.84	35300
29	Canada	5.6	29.1	11.30	31.0	40700	2.870	81.3	1.63	47400

Fourth Cluster

In [32]:
```
X[y_kmeans==3].describe()
```

Out[32]:

	child_mort	life_expec	income	gdpp
count	3.00000	3.000000	3.000000	3.000000
mean	5.00000	80.600000	93000.000000	87700.000000
std	3.46987	0.964365	31370.208798	17350.216137
min	2.80000	79.500000	62300.000000	70300.000000
25%	3.00000	80.250000	77000.000000	79050.000000
50%	3.20000	81.000000	91700.000000	87800.000000
75%	6.10000	81.150000	108350.000000	96400.000000
max	9.00000	81.300000	125000.000000	105000.000000

In [33]:

```
data_index = X[y_kmeans==3].index
Cluster4 = df.loc[data_index]
Cluster4.head()
```

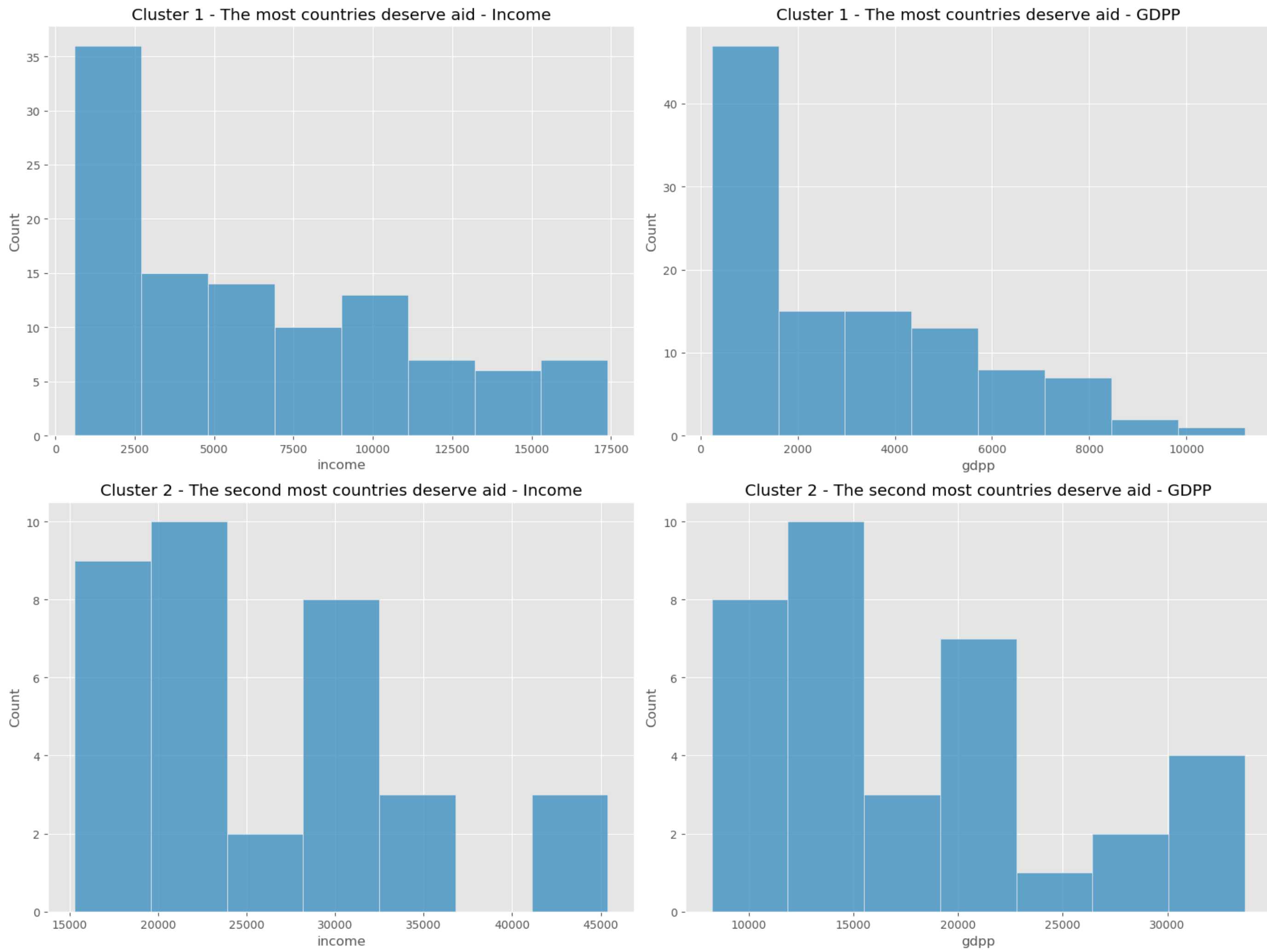
Out[33]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	children_per_woman	gdp
91	Luxembourg	2.8	175.0	7.77	142.0	91700	3.62	81.3	1.63	10500
114	Norway	3.2	39.7	9.48	28.5	62300	5.95	81.0	1.95	8780
123	Qatar	9.0	62.3	1.81	23.8	125000	6.98	79.5	2.07	7030

Visualization for the most two clusters deserving aid

In [34]:

```
fig = plt.figure(figsize=(16,12))
plt.subplot(2,2,1)
plt.title("Cluster 1 - The most countries deserve aid - Income")
sns.histplot(Cluster1["income"])
plt.subplot(2,2,2)
plt.title("Cluster 1 - The most countries deserve aid - GDPP")
sns.histplot(Cluster1["gdpp"])
plt.subplot(2,2,3)
plt.title("Cluster 2 - The second most countries deserve aid - Income")
sns.histplot(Cluster2["income"])
plt.subplot(2,2,4)
plt.title("Cluster 2 - The second most countries deserve aid - GDPP")
sns.histplot(Cluster2["gdpp"])
plt.tight_layout()
plt.show()
```



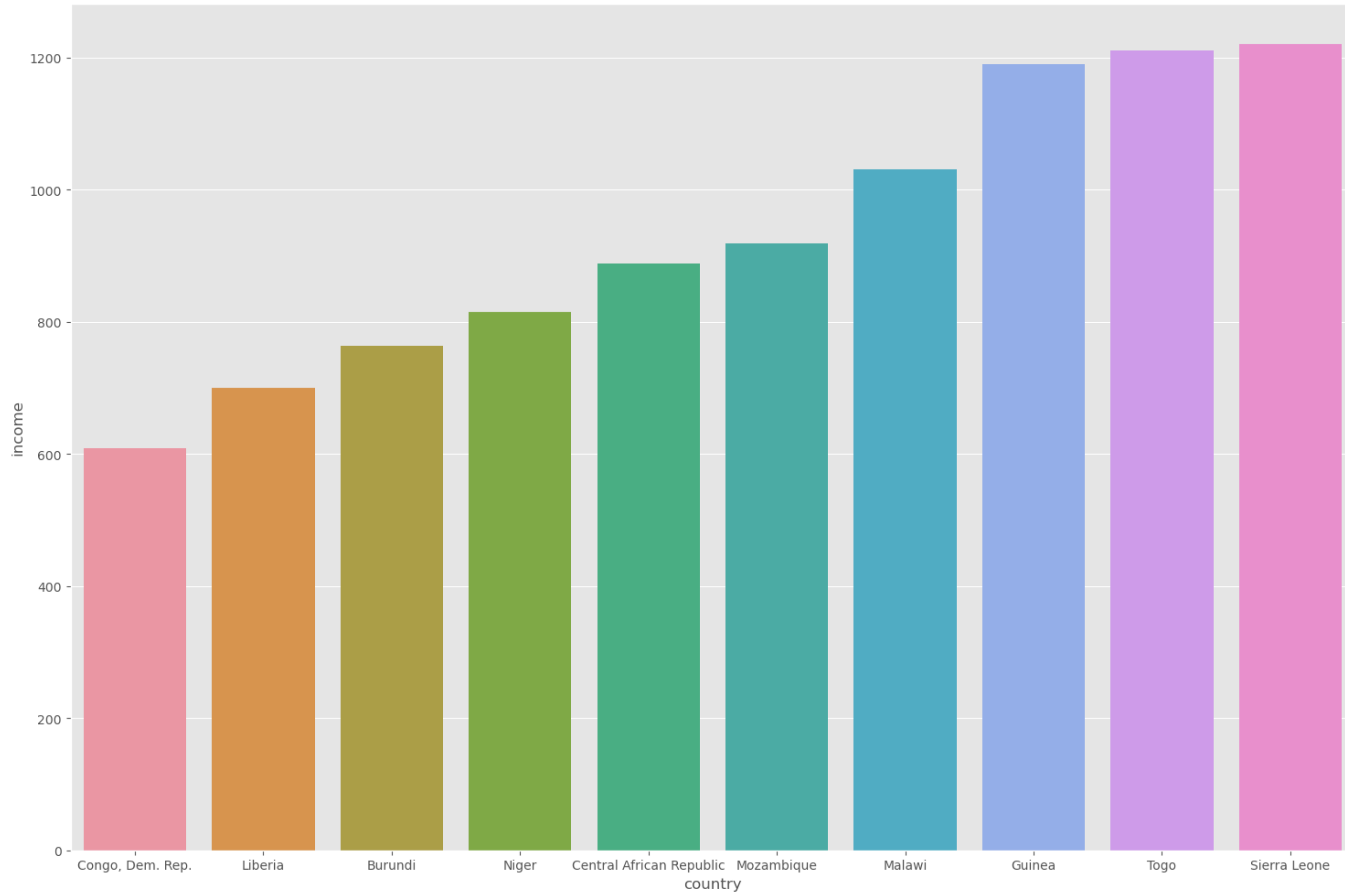
Inferences

1. Cluster 1 includes the countries that deserve the aid, the most.
2. Cluster 1, the cluster having the most poor countries, include 108 different countries.
3. Cluster 1 has very poor countries (The poorest among the poorest) that has the annual income between 1000 and 2000, and has other poor countries that the annual income is > 6000, so we want to make the priority for countries having 1000-2000

Sort countries according to income

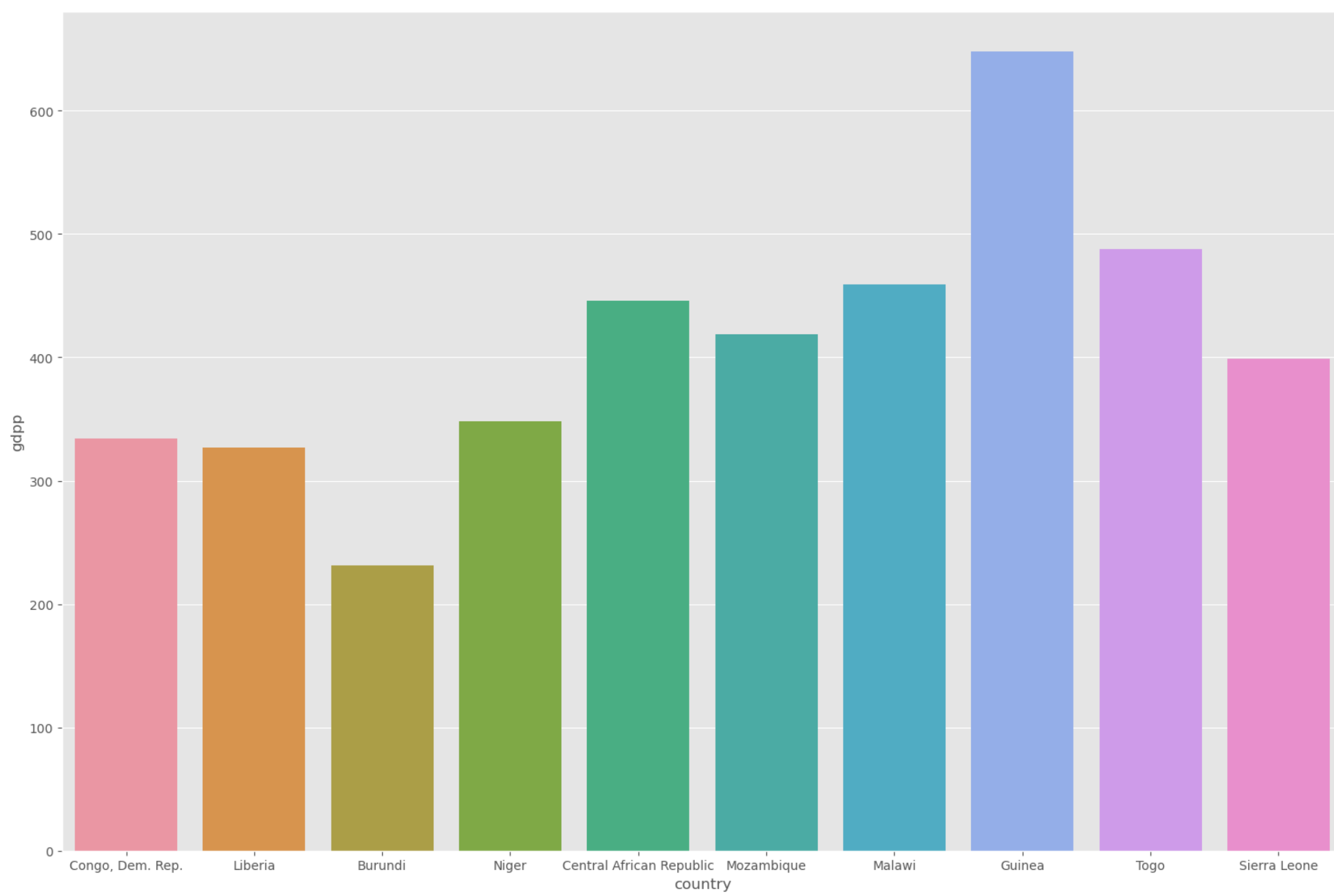
In [36]:
```
Cluster1_Sorted = Cluster1.sort_values('income')
```

In [44]:
```
fig = plt.figure(figsize=(15,10))
sns.barplot(Cluster1_Sorted["country"].head(10), Cluster1_Sorted["income"].head(10))
plt.tight_layout()
```



In [45]:

```
fig = plt.figure(figsize=(15,10))
sns.barplot(Cluster1_Sorted["country"].head(10), Cluster1_Sorted["gdpp"].head(10))
plt.tight_layout()
```



Final Results

Top 10 countries deserve the financial aid :

In [50]:
```
Cluster1_Sorted.reset_index(drop=True).head(10)
```

Out[50]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	children_per_woman	gdpp
0	Congo, Dem. Rep.	116.0	41.10	7.91	49.6	609	20.80	57.5	6.54	334
1	Liberia	89.3	19.10	11.80	92.6	700	5.47	60.8	5.02	327
2	Burundi	93.6	8.92	11.60	39.2	764	12.30	57.7	6.26	231
3	Niger	123.0	22.20	5.16	49.1	814	2.55	58.8	7.49	348
4	Central African Republic	149.0	11.80	3.98	26.5	888	2.01	47.5	5.21	446
5	Mozambique	101.0	31.50	5.21	46.2	918	7.64	54.5	5.56	419
6	Malawi	90.5	22.80	6.59	34.9	1030	12.10	53.1	5.31	459
7	Guinea	109.0	30.30	4.93	43.2	1190	16.10	58.0	5.34	648
8	Togo	90.3	40.20	7.65	57.3	1210	1.18	58.7	4.87	488
9	Sierra Leone	160.0	16.80	13.10	34.5	1220	17.20	55.0	5.20	399

We can notice that these 10 countries are really suffering from high death rates in children, bad health conditions, low annual income and life expectations during birth in range [47%-60%] only !! Also, the number of children per woman is relatively high wich indicates bad life quality, and less opportunities in education for women in these countries. Also, we can notice very very low gdpp (rarely exceeds 500) which indicates bad economical conditions.