In [2]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
import seaborn as sns
from sklearn.decomposition import PCA
```

0.) Import and Clean data

In [3]:
```python
df = pd.read_csv("Country-data.csv", sep = ",")
```

In [4]:
```python
df.head()
```

Out[4]:

	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 [5]:
```python
df.columns
```

Out[5]:
```
Index(['country', 'child_mort', 'exports', 'health', 'imports', 'income',
       'inflation', 'life_expec', 'total_fer', 'gdpp'],
      dtype='object')
```

In [6]:
```python
names = df[["country"]]
X = df.drop(["country"], axis = 1)
```

In [7]:
```python
scaler = StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

1.) Run a PCA Algorithm to get 2 Principle Components for the 9 X features

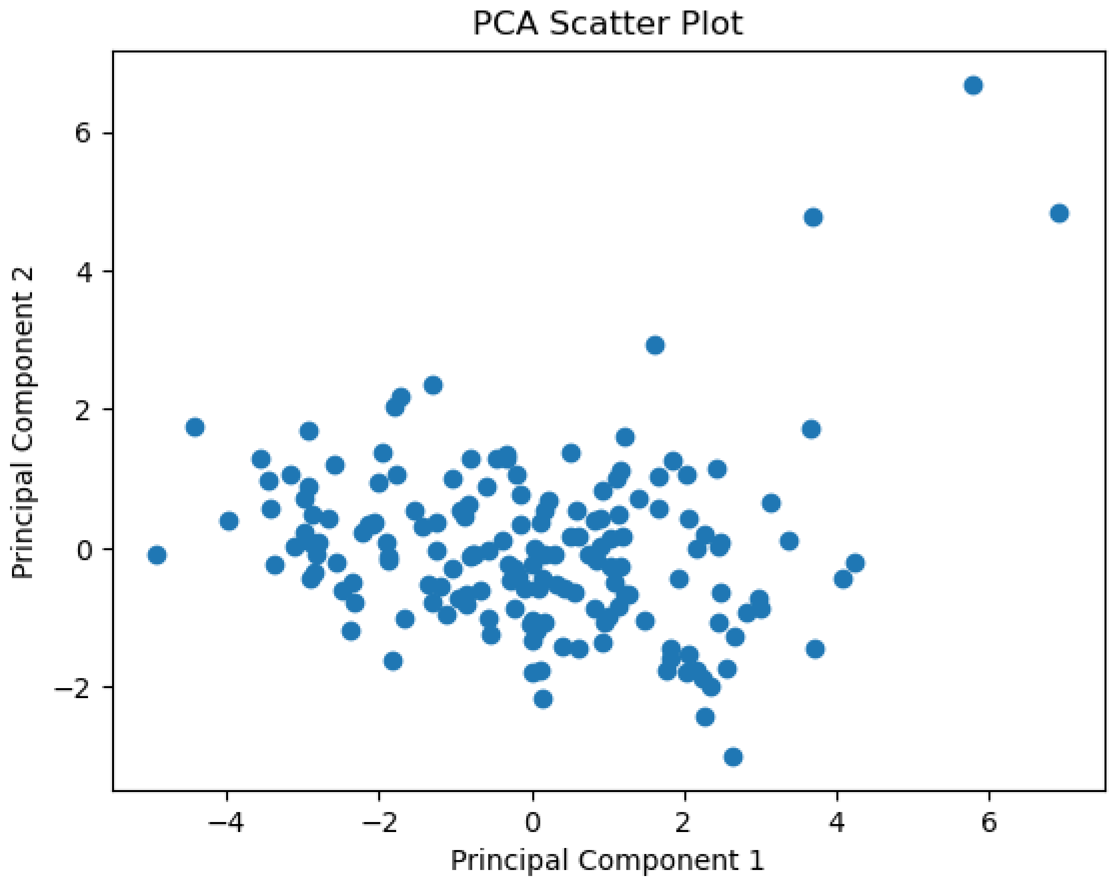
In [8]:
```python
pca = PCA(n_components=2)
```

In [9]:
```python
principal_components = pca.fit_transform(X_scaled)
```

2.) Plot a Scatter plot of the PCs on the axis

In [10]:
```python
plt.scatter(principal_components[:, 0], principal_components[:, 1])
plt.title('PCA Scatter Plot')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')

plt.show()
```



3.) Rank the features in order of importance according to PCA

In [11]:

```
loadings = np.abs(pca.components_)
importance = np.sum(loadings, axis=0)
indices = np.argsort(importance)[::-1]

print("Features ranked in order of importance according to PCA:")
for i in indices:
    print(f"Feature {i+1}: importance = {importance[i]}")
```

```
Features ranked in order of importance according to PCA:
Feature 2: importance = 0.8970604749279517
Feature 4: importance = 0.8333030860822858
Feature 7: importance = 0.6485461282474545
Feature 1: importance = 0.6124033854263231
Feature 8: importance = 0.5589620607436347
Feature 9: importance = 0.43866722007189896
Feature 5: importance = 0.4209766417758055
Feature 3: importance = 0.39392460356297726
Feature 6: importance = 0.20157740025087173
```

4.) Plot a heatmap of the feature importance

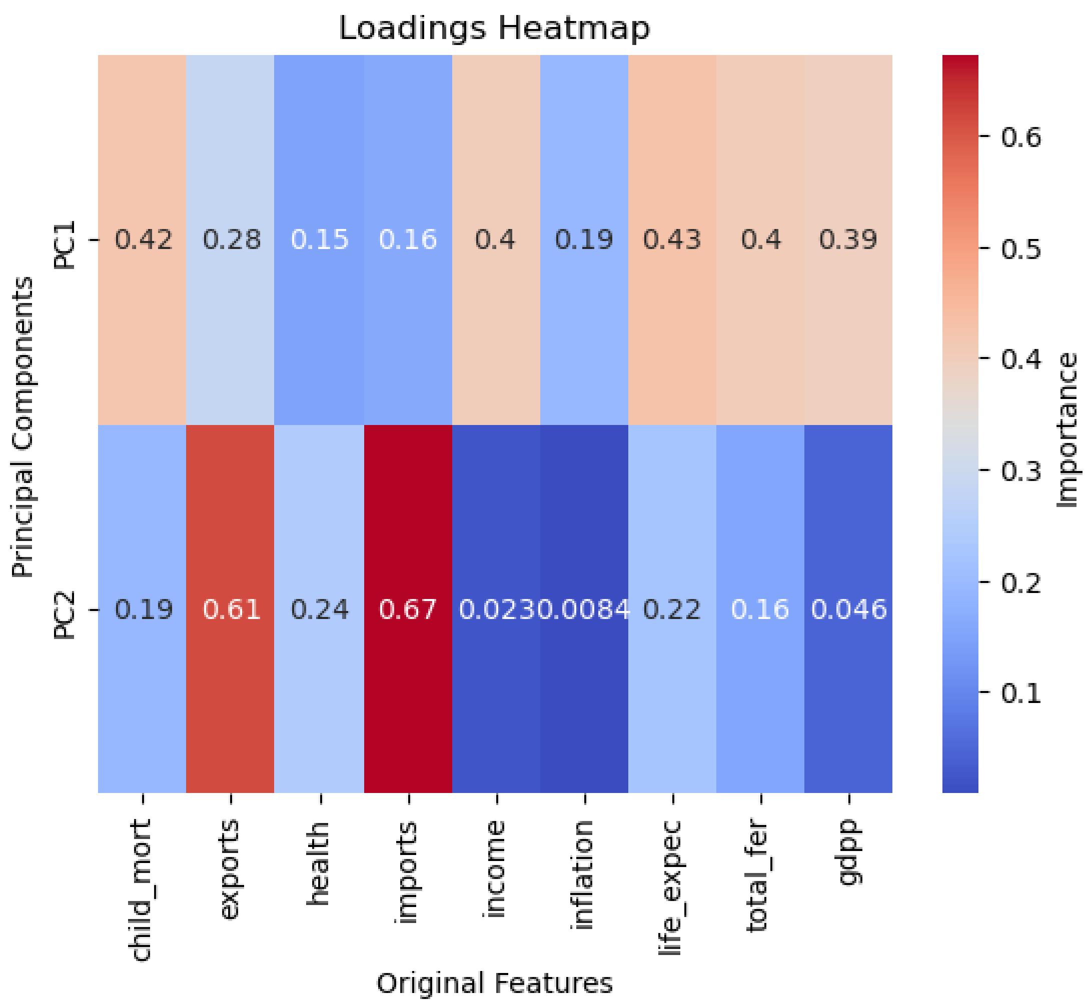
In [12]:

```
feature_names = df.columns[1:]

sns.heatmap(np.abs(pca.components_), annot= True, cmap='coolwarm', xticklabels=['child_m
       'life_expec', 'total_fer', 'gdpp'], yticklabels=['PC1', 'PC2'], cbar_kws={'label'

plt.xlabel('Original Features')
plt.ylabel('Principal Components')
```

```
plt.title('Loadings Heatmap')
plt.show()
```



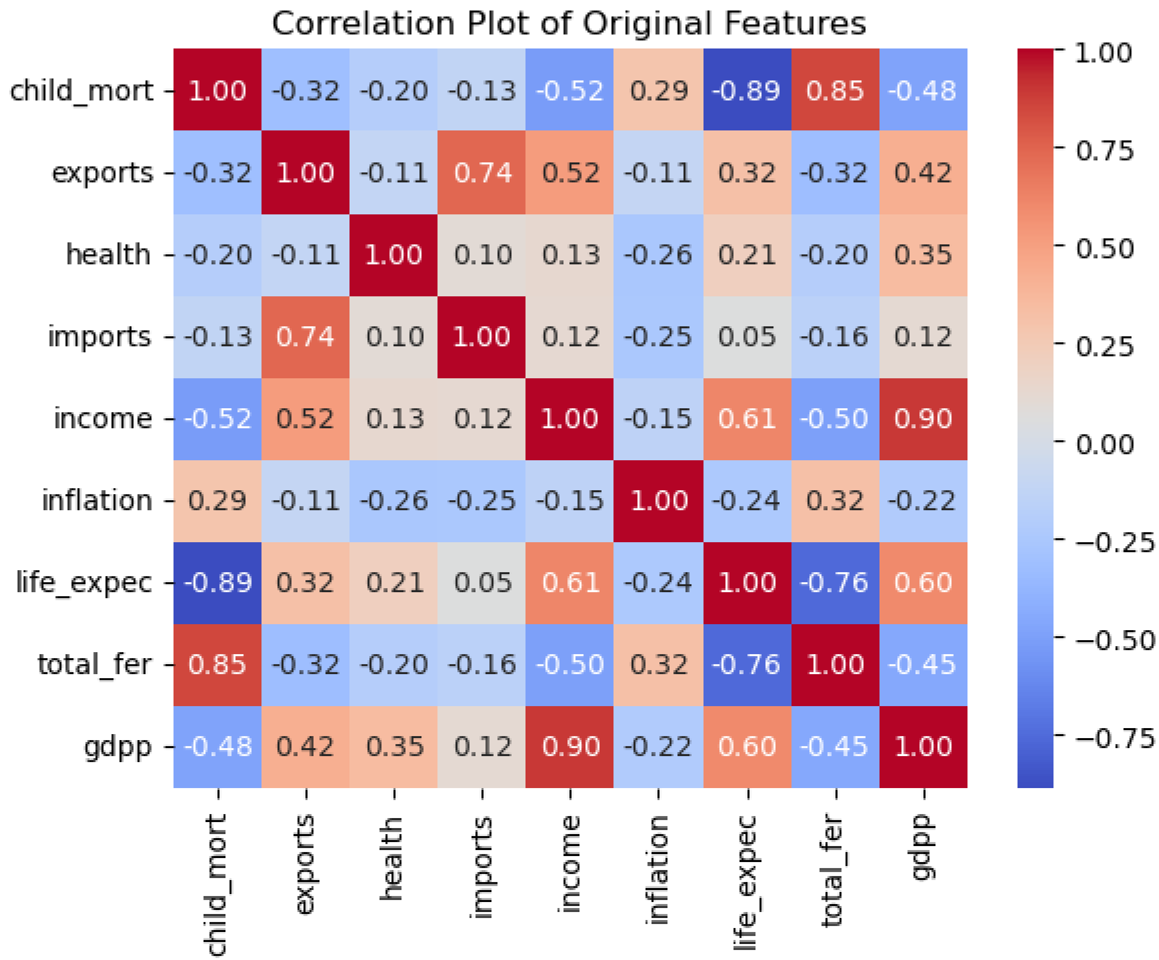
In [13]:
```
feature_names
```

Out[13]:
```
Index(['child_mort', 'exports', 'health', 'imports', 'income', 'inflation',
       'life_expec', 'total_fer', 'gdpp'],
      dtype='object')
```

5.) Plot a correlation plot of the original features. What do you notice between the graphs of 4 & 5?

In [14]:
```
corr_matrix = df.iloc[:, 1:].corr()
sns.heatmap(corr_matrix, cmap='coolwarm', annot=True, fmt='.2f')
plt.title('Correlation Plot of Original Features')

plt.show()
```



In the first graph, imports and exports stand out as the two most significant factors. However, in the second graph, their importance diminishes due to their strong correlations with other variables. This suggests that the significance of these two features may be more pronounced when considered independently.

6.) Run a PCA with 9 PCs. Plot a Cumulative Explained Variance Plot. How many PCs should we use if we want to retain 95% of the variance?

In [15]:
```
pca = PCA(n_components=9)
```

In [16]:
```
pca.fit_transform(X_scaled)
```

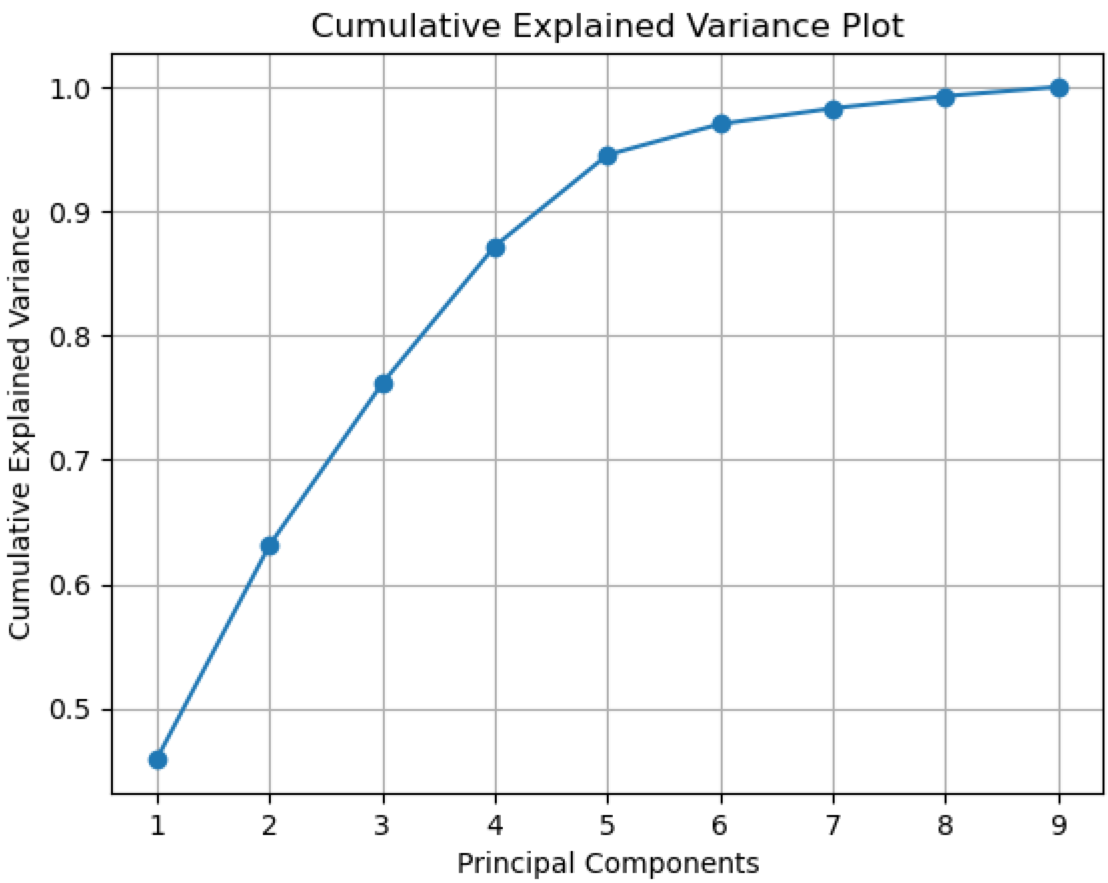
Out[16]:
```
array([[-2.91302459,  0.09562058, -0.7181185 , ...,  0.38300026,
         0.41507602, -0.01414844],
       [ 0.42991133, -0.58815567, -0.3334855 , ...,  0.24891887,
        -0.22104247,  0.17331578],
       [-0.28522508, -0.45517441,  1.22150481, ..., -0.08721359,
        -0.18416209,  0.08403718],
       ...,
       [ 0.49852439,  1.39074432, -0.23852611, ..., -0.14362677,
        -0.21759009, -0.03652231],
       [-1.88745106, -0.10945301,  1.10975159, ...,  0.06025631,
         0.08949452, -0.09604924],
       [-2.86406392,  0.48599799,  0.22316658, ..., -0.44218462,
         0.66433809, -0.44148176]])
```

In [17]:
```
pca.explained_variance_ratio_
```

Out[17]:
```
array([0.4595174 , 0.17181626, 0.13004259, 0.11053162, 0.07340211,
       0.02484235, 0.0126043 , 0.00981282, 0.00743056])
```

In [18]:
```python
cumulative_explained_variance = np.cumsum(pca.explained_variance_ratio_)

plt.plot(np.arange(1, len(cumulative_explained_variance) + 1), cumulative_explained_vari
plt.xlabel('Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Cumulative Explained Variance Plot')
plt.grid()
plt.show()
```



In [19]:
```python
np.cumsum(pca.explained_variance_ratio_)
```

Out[19]:
```
array([0.4595174 , 0.63133365, 0.76137624, 0.87190786, 0.94530998,
       0.97015232, 0.98275663, 0.99256944, 1.        ])
```

we should use 6 PCs PCA.