K Means Clustering – Life Expectancy Data

Project Description:

This project applies K-Means clustering to explore global patterns in life expectancy across countries. Using life expectancy data for males and females, the analysis seeks to uncover geographic and demographic trends that may correspond to regional health outcomes and socioeconomic development. The project involves data cleaning, outlier removal, feature transformation, geocoding of country coordinates, and visualization of clustering results on a world map. By combining geospatial and demographic dimensions, the notebook demonstrates how unsupervised learning can reveal meaningful structures in real-world public health data.

Objectives:

- Data preparation: Import, inspect, and clean the dataset to ensure consistent column names and remove any outliers that could distort clustering results. Create categorical bins for life expectancy and geocode each country to obtain latitude and longitude for spatial clustering. Visualize relationships between male and female life expectancy and identify high- and low-expectancy regions.
- Model development: Implement the K-Means clustering algorithm to group countries based on geographic location and life expectancy characteristics.
- Model evaluation: Use silhouette scores to assess the quality of clusters and determine the optimal number of clusters (k).
- Visualization of Results, Insights, Interpretation: Plot country clusters on a coordinate map and compare cluster characteristics to identify regional trends. Interpret clusters in relation to global health disparities, highlighting countries or regions with similar life expectancy profiles.

Public dataset source:

Kaggle Data Set The dataset from Worldometer provides a ranked list of countries based on life expectancy at birth, which represents the average number of years a newborn is expected to live under current mortality rates. It includes global, regional, and country-specific life expectancy figures, with separate data for males and females.

In [29]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.pipeline import Pipeline
from sklearn.cluster import KMeans
from sklearn import preprocessing
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, precision_score, recall_score, r
from sklearn.impute import SimpleImputer
```

Data Exploration and Manipulation

In [2]:
```
# Establish file path and import data
path = 'life_expectancy.csv'
df = pd.read_csv(path)
df.head(10)
```

Out[2]:

	Country	Sum of Females Life Expectancy	Sum of Life Expectancy (both sexes)	Sum of Males Life Expectancy
0	Chad	57.19	55.24	53.36
1	Nigeria	54.94	54.64	54.33
2	South Sudan	60.75	57.74	54.76
3	Lesotho	60.44	57.80	55.03
4	Central African Republic	59.56	57.67	55.51
5	Somalia	61.55	58.97	56.49
6	Burkina Faso	63.43	61.29	59.11
7	Mali	62.15	60.68	59.25
8	Benin	62.42	60.96	59.52
9	Guinea	62.09	60.90	59.66

In [45]:
```
df.describe()
```

Out[45]:

	female_LE	both_LE	male_LE
count	200.000000	200.000000	200.000000
mean	76.776900	74.133700	71.517200
std	8.820332	8.571318	8.419633
min	54.940000	54.640000	53.360000
25%	71.300000	68.732500	66.270000
50%	77.955000	74.700000	71.250000
75%	81.985000	79.062500	76.565000
max	149.220000	143.280000	137.640000

In [38]:

```
for c in df.columns:
    print(repr(c))  # shows hidden chars like '\xa0' or trailing spaces
```

```
'Country'
'Sum of Females  Life Expectancy'
'Sum of Life Expectancy  (both sexes)'
'Sum of Males  Life Expectancy'
```

In [3]:

```
# See current columns (so you can rewrite them)
print(list(df.columns))

# Provide your custom names in the exact same order
new_names = [
    "country",
    "female_LE",
    "both_LE",
    "male_LE",
]

# Assign
if len(new_names) != len(df.columns):
    raise ValueError("new_names length must match number of columns")
df.columns = new_names
df.columns
```

```
['Country', 'Sum of Females  Life Expectancy', 'Sum of Life Expectancy  (bot
h sexes)', 'Sum of Males  Life Expectancy']
```

Out[3]:

```
Index(['country', 'female_LE', 'both_LE', 'male_LE'], dtype='object')
```

In [4]:

```
# The one value for Micronesia life expectancy for males and females seems t
# Filter out outliers
mask = (df['female_LE'] >= 100) & (df['male_LE'] >= 100)
df_filter = df.loc[~mask].copy()

print("Original DataFrame:")
print(df)
print("\nDataFrame after removing outliers using IQR method:")
print(df_filter)
```

```
Original DataFrame:
                       country  female_LE  both_LE  male_LE
0                         Chad      57.19    55.24    53.36
1                      Nigeria      54.94    54.64    54.33
2                  South Sudan      60.75    57.74    54.76
3                      Lesotho      60.44    57.80    55.03
4     Central African Republic      59.56    57.67    55.51
..                         ...        ...      ...      ...
195                Switzerland      85.95    84.09    82.17
196       United Arab Emirates      84.32    83.07    82.17
197                  Australia      85.85    84.07    82.28
198                  Hong Kong      88.26    85.63    82.97
199                 Micronesia     149.22   143.28   137.64

[200 rows x 4 columns]

DataFrame after removing outliers using IQR method:
                       country  female_LE  both_LE  male_LE
0                         Chad      57.19    55.24    53.36
1                      Nigeria      54.94    54.64    54.33
2                  South Sudan      60.75    57.74    54.76
3                      Lesotho      60.44    57.80    55.03
4     Central African Republic      59.56    57.67    55.51
..                         ...        ...      ...      ...
194                     Norway      84.97    83.46    81.94
195                Switzerland      85.95    84.09    82.17
196       United Arab Emirates      84.32    83.07    82.17
197                  Australia      85.85    84.07    82.28
198                  Hong Kong      88.26    85.63    82.97

[199 rows x 4 columns]
```

In [55]:
```
df_filter.describe()
```

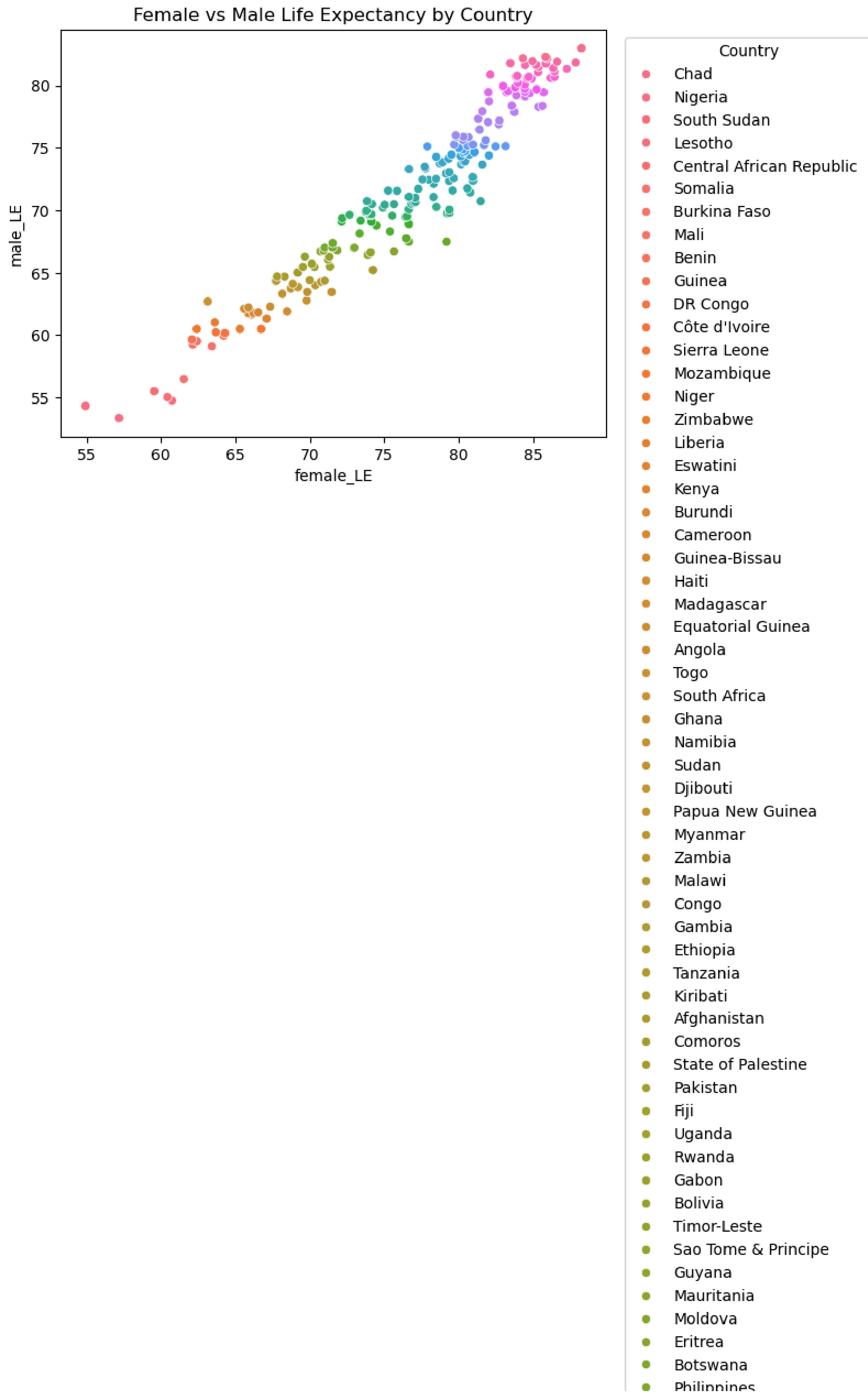
Out[55]:

	female_LE	both_LE	male_LE
count	199.000000	199.000000	199.000000
mean	76.412864	73.786231	71.184925
std	7.180037	7.040573	7.003951
min	54.940000	54.640000	53.360000
25%	71.280000	68.725000	66.270000
50%	77.910000	74.690000	71.080000
75%	81.900000	78.950000	76.230000
max	88.260000	85.630000	82.970000

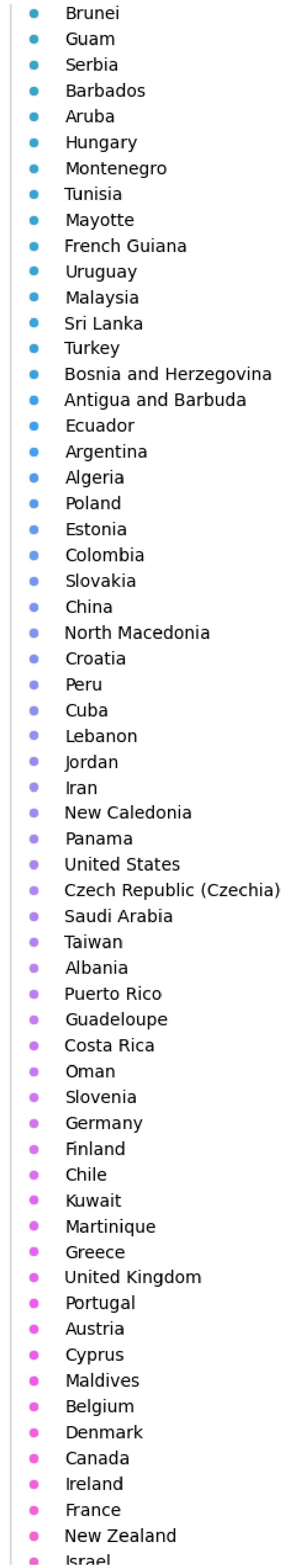
In [56]:
```
sns.scatterplot(
    data=df_filter,
    x='female_LE',
    y='male_LE',
    hue="country"
```

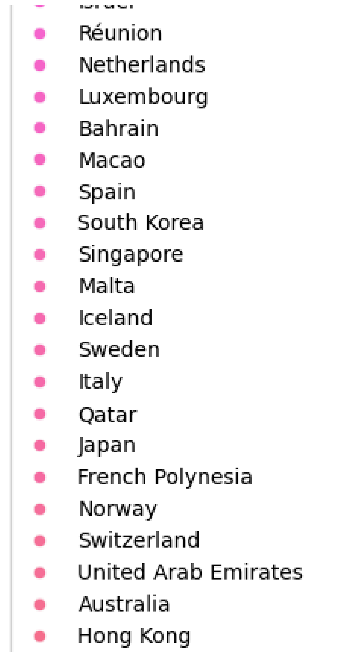
```
)
plt.title("Female vs Male Life Expectancy by Country")
plt.legend(title="Country", bbox_to_anchor=(1.02, 1))
plt.tight_layout()
plt.show()
```

```
/var/folders/cx/jsmdsr392b16bs81k3s1s4n00000gn/T/ipykernel_58202/2893806423.
py:9: UserWarning: Tight layout not applied. The bottom and top margins cann
ot be made large enough to accommodate all Axes decorations.
  plt.tight_layout()
```


Female vs Male Life Expectancy by Country
male_LE
female_LE
55
60
65
70
75
80
85
Country
Chad
Nigeria
South Sudan
Lesotho
Central African Republic
Somalia
Burkina Faso
Mali
Benin
Guinea
DR Congo
Côte d'Ivoire
Sierra Leone
Mozambique
Niger
Zimbabwe
Liberia
Eswatini
Kenya
Burundi
Cameroon
Guinea-Bissau
Haiti
Madagascar
Equatorial Guinea
Angola
Togo
South Africa
Ghana
Namibia
Sudan
Djibouti
Papua New Guinea
Myanmar
Zambia
Malawi
Congo
Gambia
Ethiopia
Tanzania
Kiribati
Afghanistan
Comoros
State of Palestine
Pakistan
Fiji
Uganda
Rwanda
Gabon
Bolivia
Timor-Leste
Sao Tome & Principe
Guyana
Mauritania
Moldova
Eritrea
Botswana

- Philippines
- Turkmenistan
- Senegal
- Laos
- Yemen
- Russia
- Mongolia
- El Salvador
- Cambodia
- Kyrgyzstan
- St. Vincent & Grenadines
- Venezuela
- Jamaica
- Nepal
- Indonesia
- Solomon Islands
- Saint Lucia
- Tonga
- Uzbekistan
- Vanuatu
- Libya
- Egypt
- Tajikistan
- Belarus
- Georgia
- Ukraine
- Western Sahara
- Samoa
- Vietnam
- Seychelles
- Syria
- Kazakhstan
- Guatemala
- Honduras
- Iraq
- Trinidad and Tobago
- Suriname
- Dominican Republic
- India
- U.S. Virgin Islands
- Paraguay
- Bahamas
- Belize
- Lithuania
- North Korea
- Bhutan
- Armenia
- Azerbaijan
- Latvia
- Mauritius
- Bulgaria
- Thailand
- Mexico
- Nicaragua
- Grenada
- Romania
- Curaçao
- Brazil
- Cabo Verde
- Bangladesh
- Morocco


Brunei
Guam
Serbia
Barbados
Aruba
Hungary
Montenegro
Tunisia
Mayotte
French Guiana
Uruguay
Malaysia
Sri Lanka
Turkey
Bosnia and Herzegovina
Antigua and Barbuda
Ecuador
Argentina
Algeria
Poland
Estonia
Colombia
Slovakia
China
North Macedonia
Croatia
Peru
Cuba
Lebanon
Jordan
Iran
New Caledonia
Panama
United States
Czech Republic (Czechia)
Saudi Arabia
Taiwan
Albania
Puerto Rico
Guadeloupe
Costa Rica
Oman
Slovenia
Germany
Finland
Chile
Kuwait
Martinique
Greece
United Kingdom
Portugal
Austria
Cyprus
Maldives
Belgium
Denmark
Canada
Ireland
France
New Zealand
Israel



In [5]:

```
# Create bins for life expectancy values so that they are categorical
# Define custom bins and labels
bins = [50,60,70,80,90]
labels = ['50-60', '60-70', '70-80', '80-90']

# Create a new categorical column
df_filter['life_expectancy_male'] = pd.cut(df_filter['male_LE'], bins=bins,
df_filter['life_expectancy_female'] = pd.cut(df_filter['female_LE'], bins=bi

print(df_filter)
```

```
                       country  female_LE  both_LE  male_LE  \
0                         Chad      57.19    55.24    53.36
1                      Nigeria      54.94    54.64    54.33
2                  South Sudan      60.75    57.74    54.76
3                      Lesotho      60.44    57.80    55.03
4     Central African Republic      59.56    57.67    55.51
..                         ...        ...      ...      ...
194                     Norway      84.97    83.46    81.94
195                Switzerland      85.95    84.09    82.17
196       United Arab Emirates      84.32    83.07    82.17
197                  Australia      85.85    84.07    82.28
198                  Hong Kong      88.26    85.63    82.97

    life_expectancy_male life_expectancy_female
0                  50-60                  50-60
1                  50-60                  50-60
2                  50-60                  60-70
3                  50-60                  60-70
4                  50-60                  50-60
..                   ...                    ...
194                80-90                  80-90
195                80-90                  80-90
196                80-90                  80-90
197                80-90                  80-90
198                80-90                  80-90

[199 rows x 6 columns]
```

In [10]:
```
countries = df_filter['country'].unique().tolist()
len(countries)
```

Out[10]: 199

In [78]:
```
countries
```

```
Out[78]: ['Chad',
 'Nigeria',
 'South Sudan',
 'Lesotho',
 'Central African Republic',
 'Somalia',
 'Burkina Faso',
 'Mali',
 'Benin',
 'Guinea',
 'DR Congo',
 "Côte d'Ivoire",
 'Sierra Leone',
 'Mozambique',
 'Niger',
 'Zimbabwe',
 'Liberia',
 'Eswatini',
 'Kenya',
 'Burundi',
 'Cameroon',
 'Guinea-Bissau',
 'Haiti',
 'Madagascar',
 'Equatorial Guinea',
 'Angola',
 'Togo',
 'South Africa',
 'Ghana',
 'Namibia',
 'Sudan',
 'Djibouti',
 'Papua New Guinea',
 'Myanmar',
 'Zambia',
 'Malawi',
 'Congo',
 'Gambia',
 'Ethiopia',
 'Tanzania',
 'Kiribati',
 'Afghanistan',
 'Comoros',
 'State of Palestine',
 'Pakistan',
 'Fiji',
 'Uganda',
 'Rwanda',
 'Gabon',
 'Bolivia',
 'Timor-Leste',
 'Sao Tome & Principe',
 'Guyana',
 'Mauritania',
 'Moldova',
 'Eritrea',
```

```
'Botswana',
'Philippines',
'Turkmenistan',
'Senegal',
'Laos',
'Yemen',
'Russia',
'Mongolia',
'El Salvador',
'Cambodia',
'Kyrgyzstan',
'St. Vincent & Grenadines',
'Venezuela',
'Jamaica',
'Nepal',
'Indonesia',
'Solomon Islands',
'Saint Lucia',
'Tonga',
'Uzbekistan',
'Vanuatu',
'Libya',
'Egypt',
'Tajikistan',
'Belarus',
'Georgia',
'Ukraine',
'Western Sahara',
'Samoa',
'Vietnam',
'Seychelles',
'Syria',
'Kazakhstan',
'Guatemala',
'Honduras',
'Iraq',
'Trinidad and Tobago',
'Suriname',
'Dominican Republic',
'India',
'U.S. Virgin Islands',
'Paraguay',
'Bahamas',
'Belize',
'Lithuania',
'North Korea',
'Bhutan',
'Armenia',
'Azerbaijan',
'Latvia',
'Mauritius',
'Bulgaria',
'Thailand',
'Mexico',
'Nicaragua',
'Grenada',
```

```
'Romania',
'Curaçao',
'Brazil',
'Cabo Verde',
'Bangladesh',
'Morocco',
'Brunei',
'Guam',
'Serbia',
'Barbados',
'Aruba',
'Hungary',
'Montenegro',
'Tunisia',
'Mayotte',
'French Guiana',
'Uruguay',
'Malaysia',
'Sri Lanka',
'Turkey',
'Bosnia and Herzegovina',
'Antigua and Barbuda',
'Ecuador',
'Argentina',
'Algeria',
'Poland',
'Estonia',
'Colombia',
'Slovakia',
'China',
'North Macedonia',
'Croatia',
'Peru',
'Cuba',
'Lebanon',
'Jordan',
'Iran',
'New Caledonia',
'Panama',
'United States',
'Czech Republic (Czechia)',
'Saudi Arabia',
'Taiwan',
'Albania',
'Puerto Rico',
'Guadeloupe',
'Costa Rica',
'Oman',
'Slovenia',
'Germany',
'Finland',
'Chile',
'Kuwait',
'Martinique',
'Greece',
'United Kingdom',
```

```
 'Portugal',
 'Austria',
 'Cyprus',
 'Maldives',
 'Belgium',
 'Denmark',
 'Canada',
 'Ireland',
 'France',
 'New Zealand',
 'Israel',
 'Réunion',
 'Netherlands',
 'Luxembourg',
 'Bahrain',
 'Macao',
 'Spain',
 'South Korea',
 'Singapore',
 'Malta',
 'Iceland',
 'Sweden',
 'Italy',
 'Qatar',
 'Japan',
 'French Polynesia',
 'Norway',
 'Switzerland',
 'United Arab Emirates',
 'Australia',
 'Hong Kong']
```

In [6]:
```
from geopy.geocoders import Nominatim
from geopy.exc import GeocoderTimedOut

geolocator = Nominatim(user_agent="empower_lab")

def get_country_coordinates(country_name):
        try:
            location = geolocator.geocode(country_name, timeout=10) # Set a
            if location:
                return location.latitude, location.longitude
            else:
                return None, None
        except GeocoderTimedOut:
            print(f"Geocoding timed out for: {country_name}. Retrying...")
            return get_country_coordinates(country_name) # Retry on timeout
        except Exception as e:
            print(f"Error geocoding {country_name}: {e}")
            return None, None
```

In [7]:
```
df0 = df_filter.copy()
```

In [11]:
```
def chunk_and_geocode(countries, get_country_coordinates, chunk_size=50): #
```

```
    dfs = []

    for i in range(0, len(countries), chunk_size): # from 0 to len(countries
        chunk = countries[i:i + chunk_size] # establish which chunk of count
        df0 = pd.DataFrame({'country': chunk}) # create a dataframe with tha
        df0[['Latitude', 'Longitude']] = df0['country'].apply( # find long a
            lambda x: pd.Series(get_country_coordinates(x))
        )
        dfs.append(df0) # appends each df chunk
    return dfs

dfs = chunk_and_geocode(countries, get_country_coordinates)
```

In [13]:

```
# Combine dfs
all_countries_df = pd.concat(dfs, axis=0)
```

In [14]:

```
# Match countries from new combined countries DF to the original df_filter
# Merge on the 'country' column
merged_df = df0.merge(all_countries_df, on='country', how='left') # keep all
```

In [154…

```
merged_df
```

Out[154…

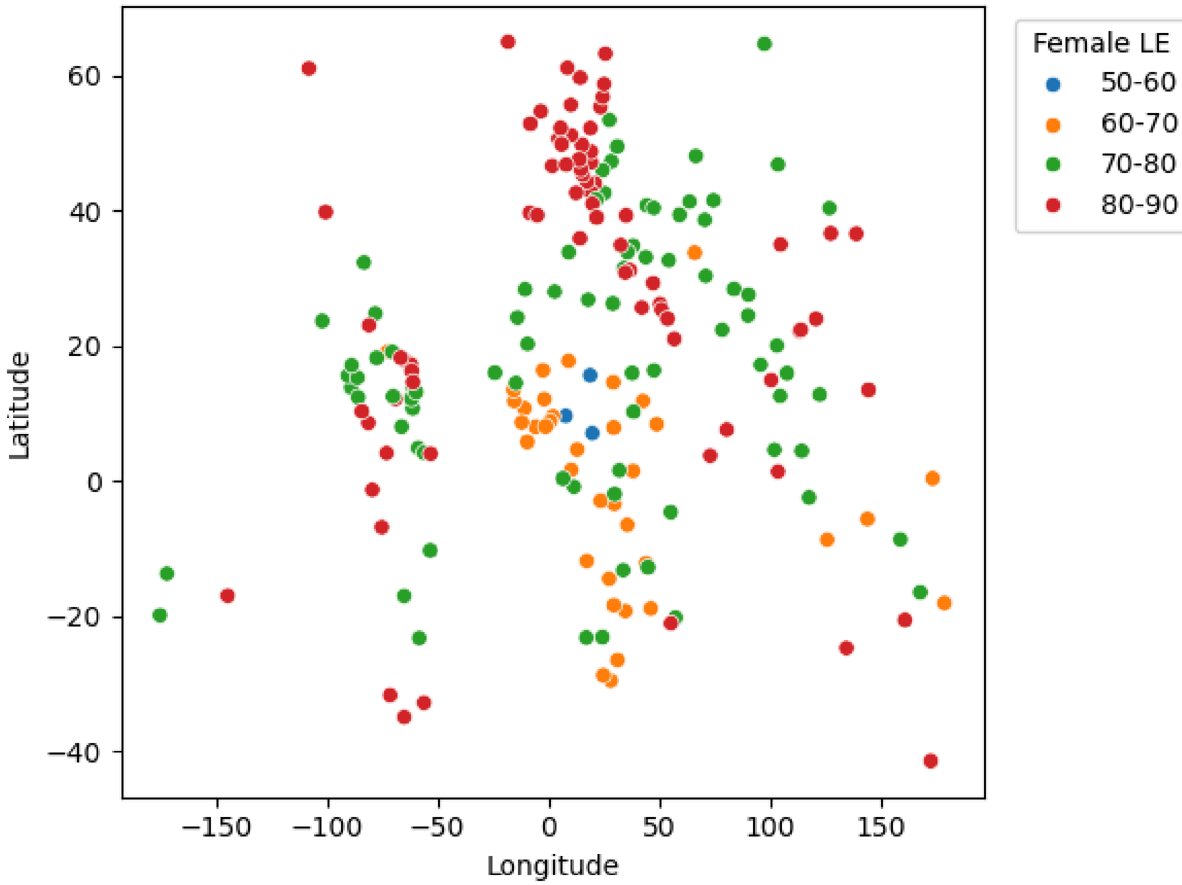
	country	female_LE	both_LE	male_LE	life_expectancy_male	life_expectancy_
0	chad	57.19	55.24	53.36	50-60	
1	nigeria	54.94	54.64	54.33	50-60	
2	south sudan	60.75	57.74	54.76	50-60	
3	lesotho	60.44	57.80	55.03	50-60	
4	central african republic	59.56	57.67	55.51	50-60	
...	...	...	...	...	...	
194	norway	84.97	83.46	81.94	80-90	
195	switzerland	85.95	84.09	82.17	80-90	
196	united arab emirates	84.32	83.07	82.17	80-90	
197	australia	85.85	84.07	82.28	80-90	
198	hong kong	88.26	85.63	82.97	80-90	

199 rows × 8 columns

In [38]:

```
sns.scatterplot(
    data=merged_df,
    x='Longitude',
    y='Latitude',
```

```
    hue="life_expectancy_female"
)
# plt.title("Female vs Male Life Expectancy by Country")
plt.legend(title="Female LE", bbox_to_anchor=(1.02, 1))
plt.tight_layout()
plt.show()
```



Bulding the Model

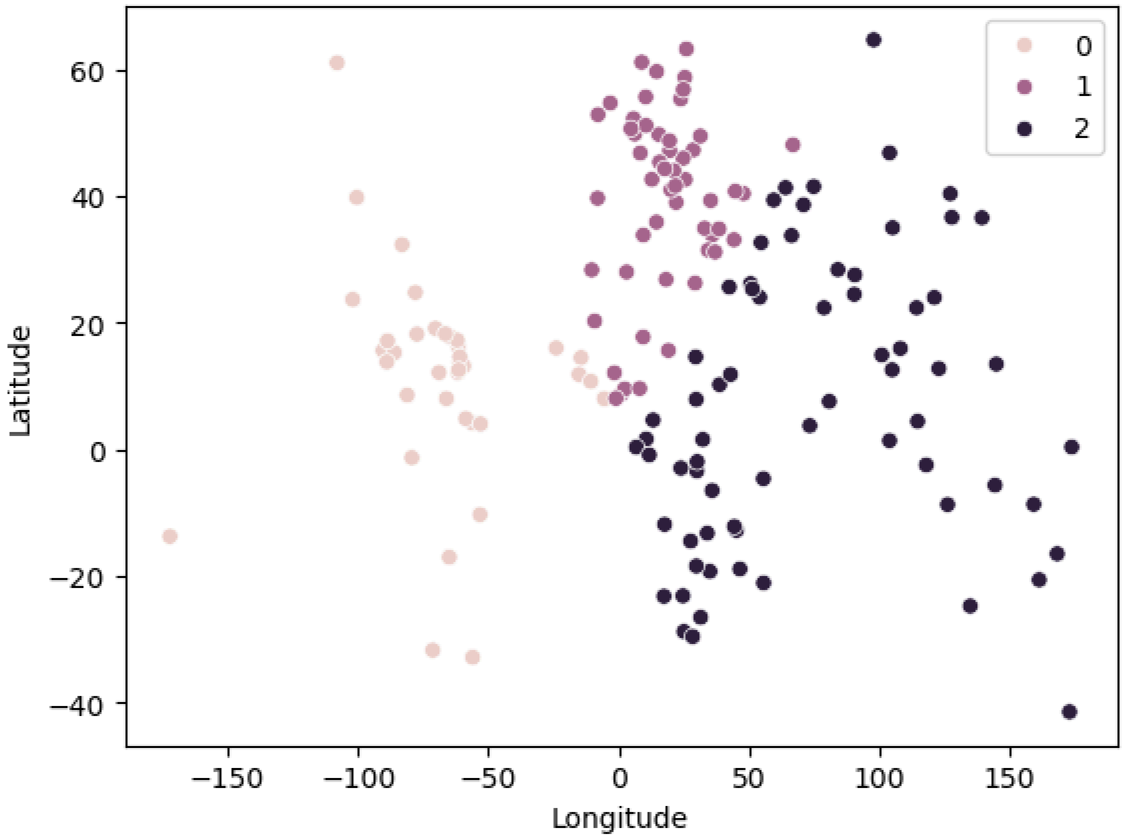
In [23]:
```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(merged_df[['Latitude', '

# Normalize the training and test data
X_train_norm = preprocessing.normalize(X_train)
X_test_norm = preprocessing.normalize(X_test)
```

In [34]:
```
# Arbitrarily choose a number of clusters
# Create instance of kmeans
kmeans = KMeans(n_clusters=3, random_state=0, n_init='auto')
# Fit the model to the normalized trainign data
kmeans.fit(X_train_norm)
```

Out[34]:
```
KMeans
KMeans(n_clusters=3, random_state=0)
```

In [35]:
```
# Visualize the data fit
sns.scatterplot(data = X_train, x = 'Longitude', y = 'Latitude', hue = kmear
```

Out[35]: <Axes: xlabel='Longitude', ylabel='Latitude'>



In [ ]:
```
# A silhouette score is a matric from evaluating the quality of clusters in
# A higher score indicates that clusters are well-separated and data points

silhouette_score(X_train_norm, kmeans.labels_, metric='euclidean')
# Score is satisfactory (greater than 0.5)
```

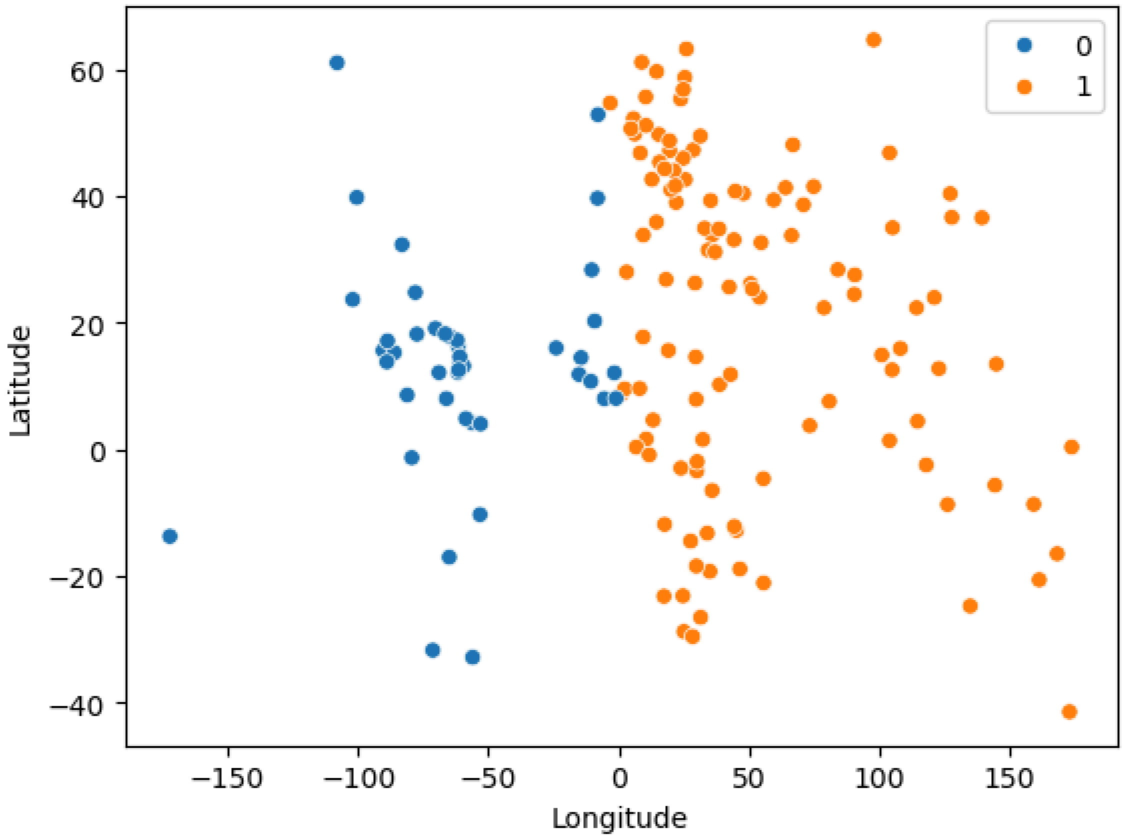
Out[ ]: 0.6269966700539663

Finding the best value of k

In [37]:
```
# Try a different range of k value
K = range(2,8)
fits = []
score =  []

for k in K:
    # train and fit the model
    model = KMeans(n_clusters=k, random_state=0, n_init='auto').fit(X_train_
    # append the model fit
    fits.append(model)
    # append the score of the mode
    score.append(silhouette_score(X_train_norm, model.labels_, metric='eucli
```

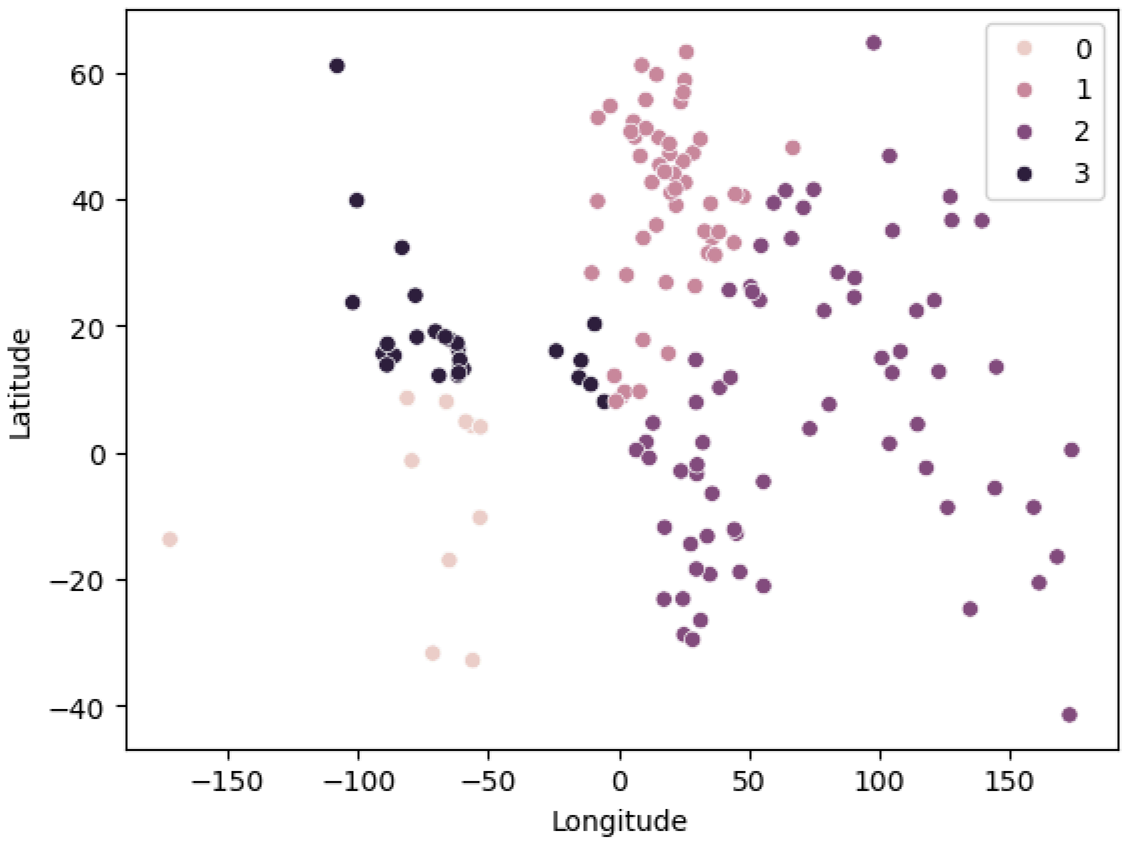
In [ ]:
```python
# Look at when k=2
sns.scatterplot(data = X_train, x = 'Longitude', y = 'Latitude', hue = fits[
```

Out[ ]: <Axes: xlabel='Longitude', ylabel='Latitude'>



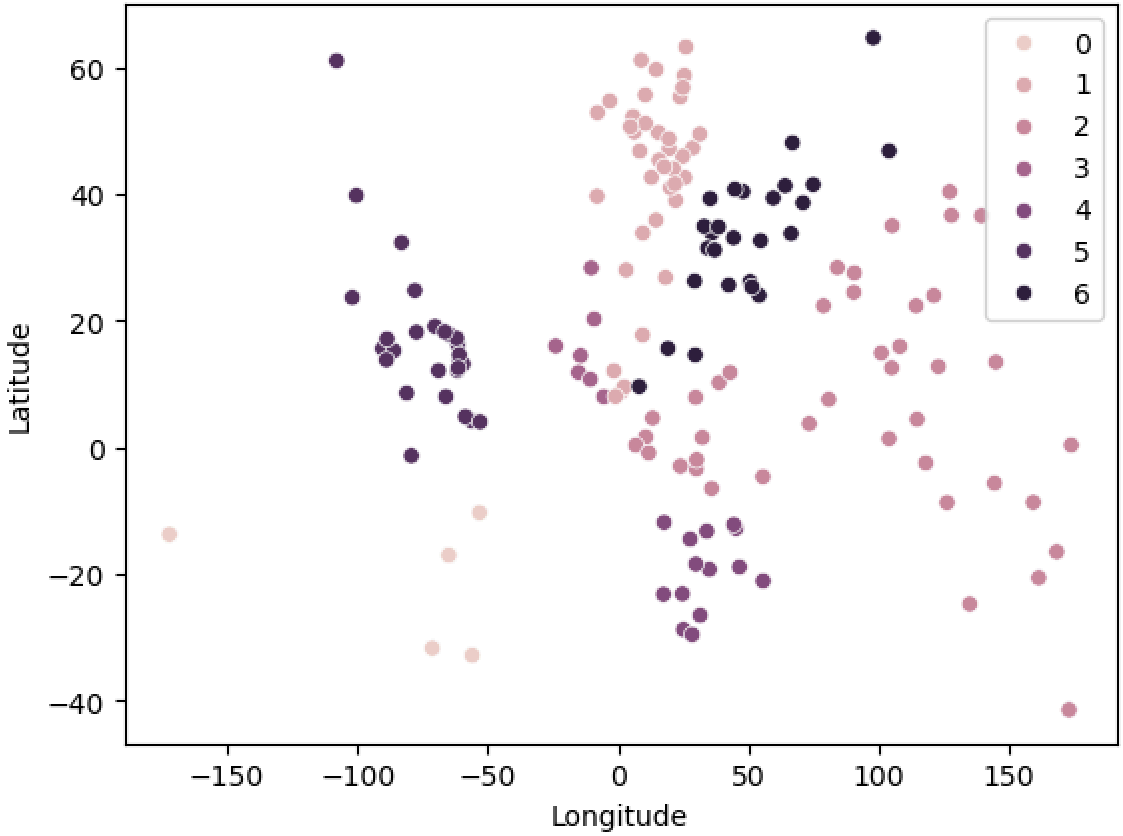
In [40]:
```python
# Look at when k=4
sns.scatterplot(data = X_train, x = 'Longitude', y = 'Latitude', hue = fits[
```

Out[40]: <Axes: xlabel='Longitude', ylabel='Latitude'>



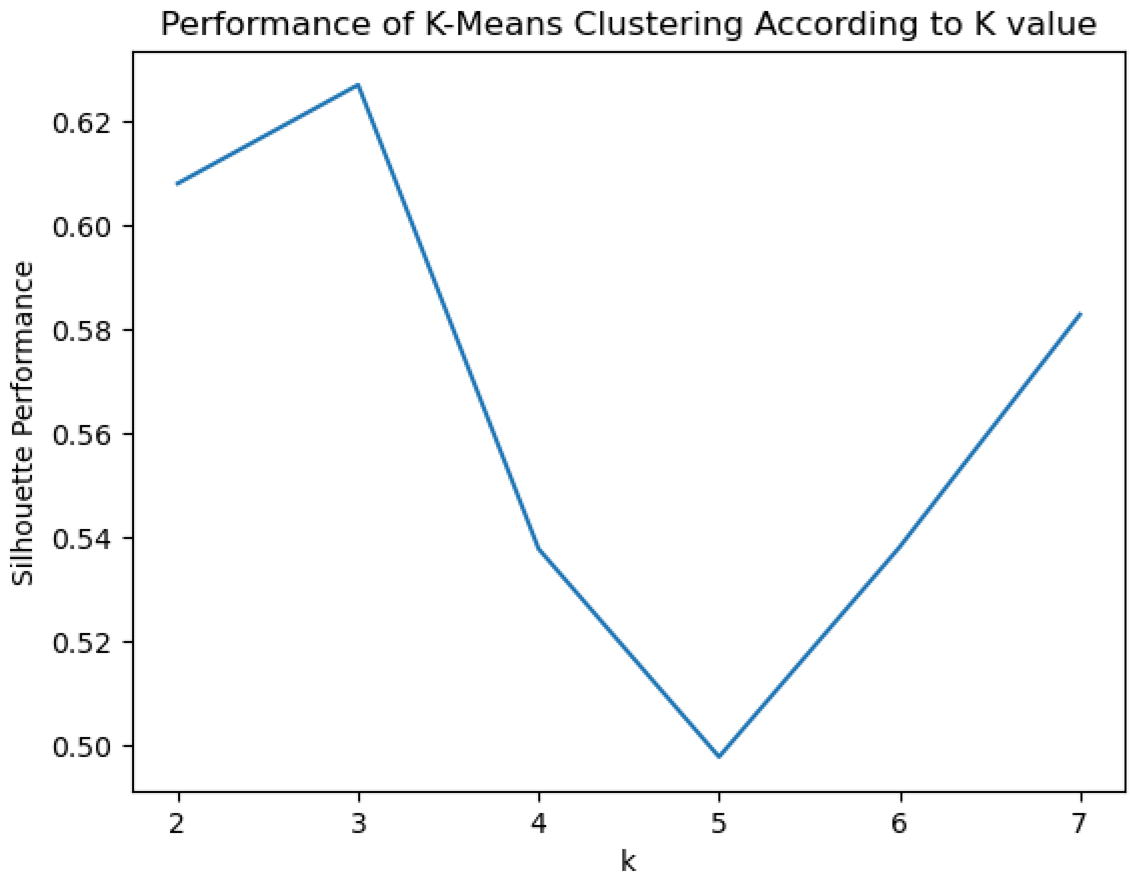
In [45]:
```
# Look at k=7
sns.scatterplot(data = X_train, x = 'Longitude', y = 'Latitude', hue = fits[
```

Out[45]: `<Axes: xlabel='Longitude', ylabel='Latitude'>`



k=2 does not capture the nuances of the life expectancy across countries. While k=7 has too man clusters.

In [56]:
```
# Let's visualize k's by score performance
ax = sns.lineplot(x = K, y = score)
ax.set_title("Performance of K-Means Clustering According to K value")
ax.set(xlabel='k', ylabel='Silhouette Performance')

plt.show()
```



We can see improvements in clusters until k=3, then the model has diminishing returns and worse performance until k=5. Overfitting causes the model to then begin improving again.

Interpretation and Insights

- Low life expectancy seemns to mostly cluster around Africa and parts of South Asia. Male and female life expectancy values tend to fall in the 50–60 year range.

These regions often face limited healthcare infrastructure, higher infectious disease burden, and economic constraints.

- Clusters for life expectancy between 65-75 years encompass many Latin American, Middle Eastern, and Southeast Asian countries.

These countries are in transitional stages of development, balancing improvements in healthcare access with ongoing challenges such as chronic disease and inequality.

- Countries with the clusters of highest life expectancy are developed regions, including Western Europe, North America, Australia, Japan, and other high-income economies.