Global Trends in Mental Health Disorders: An Exploratory Data Analysis

In this data analysis, we explored the "Mental Health Depression Disorder" dataset, which provides comprehensive information on the prevalence of various mental health disorders across different countries over multiple years. This dataset includes data on schizophrenia, bipolar disorder, eating disorders, anxiety disorders, drug use disorders, depression, and alcohol use disorders. Our analysis aimed to uncover trends in mental health disorders, compare the prevalence of different disorders across countries, and identify potential correlations between these disorders. We also applied machine learning techniques to identify clusters of countries with similar prevalence rates.

Data Cleaning and Preparation

1. Load the Dataset

```
In [5]: import pandas as pd # Load the dataset
file_path = 'C:\\Users\\YOURPATH\\Mental health Depression disorder Data.xlsx'
data = pd.read_excel(file_path)

data.head()
```

Afghanistan AFG 1991 0.160312 0.697961 0.099313 4.829740 2 4.079531 0.671768 Afghanistan AFG 1992 0.160135 0.698107 0.096692 4.831108 1.68474 4.088358 0.670644 Afghanistan AFG 1993 0.160037 0.698257 0.094336 4.830864 6 4.096190 0.669738 Afghanistan AFG 1994 0.160022 0.698469 0.092439 4.829423 1.69433 4.099582 0.669260	Entity Code Year (%) disorders									
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2. Handle Missing Values

In [6]: # Check for missing values
 missing_values = data.isnull().sum()
 print("Missing values in each column:\n", missing_values)

Fill missing values with the mean of each column
 data_filled = data.fillna(data.mean())

Verify that there are no more missing values
 print("Missing values after filling:\n", data_filled.isnull().sum())

Missing values in each column: Entity 980 Code Schizophrenia (%) Bipolar disorder (%) Eating disorders (%) Anxiety disorders (%) Drug use disorders (%) Depression (%) Alcohol use disorders (%) dtype: int64 Missing values after filling: Entity 0 Code 980 Schizophrenia (%) Bipolar disorder (%) Eating disorders (%) Anxiety disorders (%) Drug use disorders (%) Depression (%) Alcohol use disorders (%) dtype: int64

```
In [7]: data = data.drop(columns=['Code'])
    missing_values = data.isnull().sum()
```

print("Missing values after dropping 'Code' column:\n", missing_values)

Missing values after dropping 'Code' column: Entity 0

Year 0
Schizophrenia (%) 0
Bipolar disorder (%) 0
Eating disorders (%) 0
Anxiety disorders (%) 0
Drug use disorders (%) 0
Depression (%) 0
Alcohol use disorders (%) 0

dtype: int64

3. Normalize Data

In [8]: from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

columns_to_normalize = data.columns.difference(['Entity', 'Year'])
data_normalized = data.copy()
data_normalized[columns_to_normalize] = scaler.fit_transform(data[columns_to_normalize])

data_normalized.head()

Out[8]:

:	Entity	Year	Schizophrenia (%)	Bipolar disorder (%)	Eating disorders (%)	Anxiety disorders (%)	Drug use disorders (%)	Depression (%)	Alcohol use disorders (%)
_	Afghanistan	199	0.059848	0.429617	0.032120	0.404012	0.421474	0.432891	0.044844
1	Afghanistan	0	0.058763	0.429820	0.029199	0.404144	0.423972	0.434616	0.044718
'	Afghanistan	199	0.057987	0.429984	0.026186	0.404341	0.427096	0.436594	0.044494
3	Afghanistan	1	0.057560	0.430152	0.023478	0.404305	0.430676	0.438349	0.044314
	Afghanistan	199	0.057494	0.430390	0.021299	0.404098	0.434179	0.439109	0.044219
4	+	2							
		199							

Exploratory Data Analysis (EDA)

1. Descriptive Statistics

In [9]: data_normalized.describe()

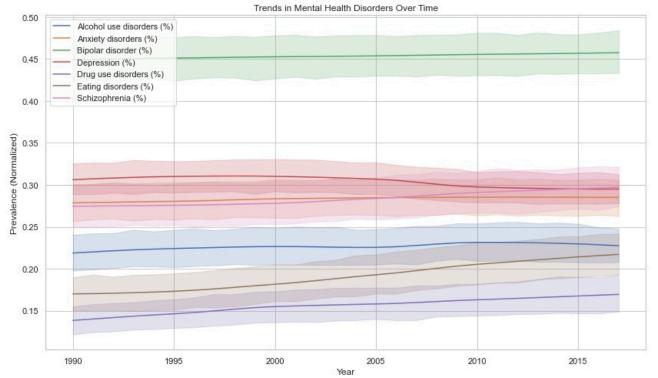
Out[9]:

:		Year	Schizophrenia (%)	Bipolar disorder (%)	Eating disorders (%)	Anxiety disorders (%)	Drug use disorders (%)	Depression (%)	Alcohol use disorders (%)
	ount	6468.000000	6468.000000	6468.000000	6468.000000	6468.000000	6468.000000	6468.000000	6468.000000
	nean	2003.500000	0.283697	0.453568	0.190891	0.283201	0.155964	0.304234	0.226520
11	std	8.078372	0.193915	0.192350	0.181754	0.168136	0.150116	0.146960	0.171108
	min	1990.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
		1996.750000	0.151738	0.337418	0.055718	0.167834	0.049339	0.193963	0.108746
	25%	2003.500000	0.230760	0.424410	0.124835	0.220477	0.111697	0.304671	0.205460
	50%	2010.250000	0.392026	0.583511	0.251423	0.382891	0.181342	0.397163	0.282612
	75%	2017.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
	max		2.000000	2.000000	1.00000	2.00000	2,000000	2,00000	2.00000

2. Visualizing Trends Over Time

```
import matplotlib.pyplot as plt
import seaborn as sns
# Set the style of the visualization
sns.set(style="whitegrid")
# Plot trends over time for each disorder
plt.figure(figsize=(14, 8))
for column in columns_to_normalize:
    sns.lineplot(x='Year', y=column, data=data_normalized, label=column)
```

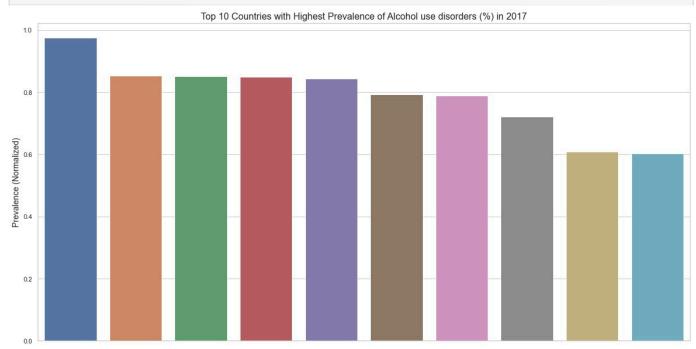


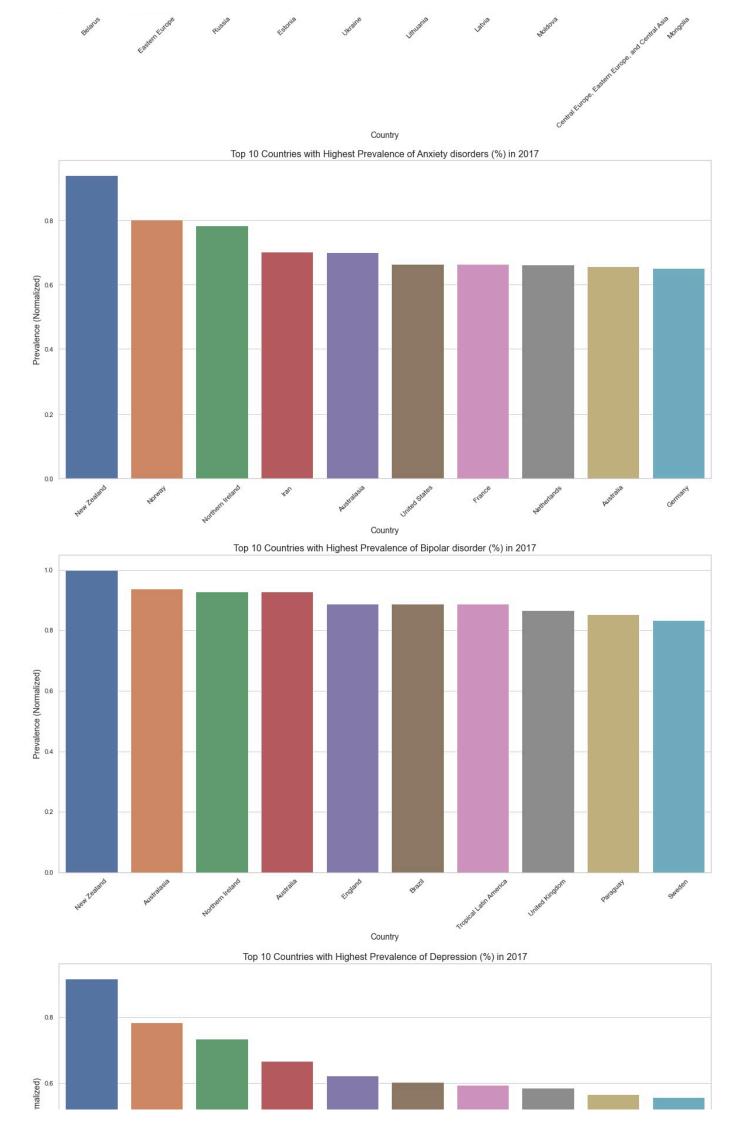


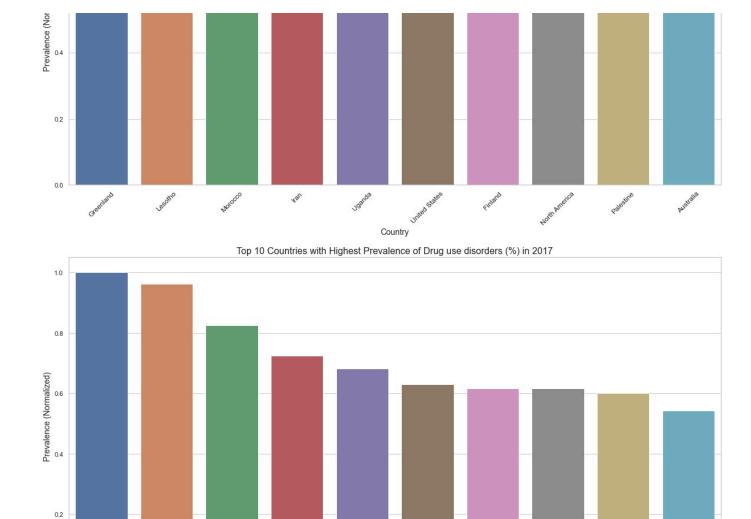
Observation: Anxiety disorders and depression have steadily increased, emphasizing the growing impact on mental health. Drug use disorders show fluctuations but an overall rise. Meanwhile, bipolar disorder, eating disorders, and schizophrenia exhibit relatively stable trends.

3. Comparing Prevalence Across Countries

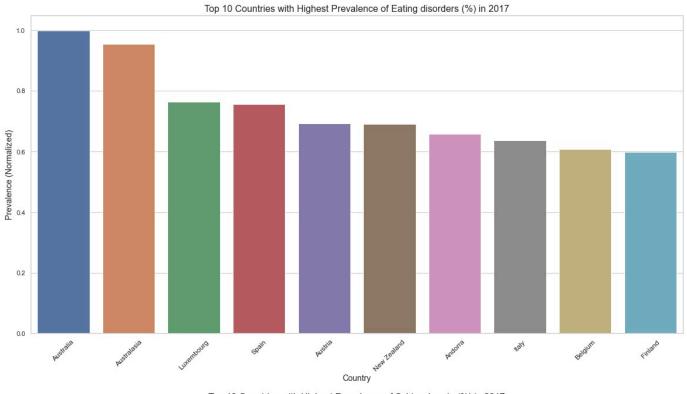
```
In [11]:
    year_to_compare = 2017
    data_year = data_normalized[data_normalized['Year'] == year_to_compare]
# Plot prevalence across countries for each disorder with improved readability
for column in columns_to_normalize:
    plt.figure(figsize=(20, 10))
    top_countries = data_year.nlargest(10, column)
    sns.barplot(x='Entity', y=column, data=top_countries)
    plt.title(f'Top 10 Countries with Highest Prevalence of {column} in {year_to_compare}', fontsize=16)
    plt.xlabel('Country', fontsize=14)
    plt.ylabel('Prevalence (Normalized)', fontsize=14)
    plt.xticks(rotation=45, fontsize=12)
    plt.show()
```





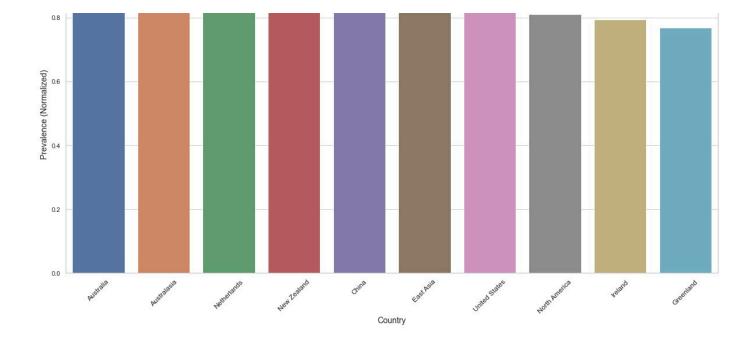


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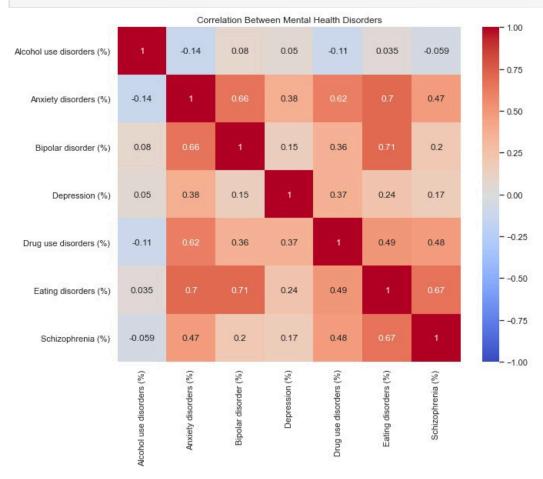


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Top 10 Countries with Highest Prevalence of Schizophrenia (%) in 2017



4. Correlation Analysis



Observation:

Strong Positive Correlations: Anxiety disorders and bipolar disorder (0.66), eating disorders and schizophrenia (0.67), and eating disorders and bipolar disorder (0.71).

Moderate Positive Correlations: Anxiety disorders and depression (0.38), drug use disorders and anxiety disorders (0.62), and depression and bipolar disorder (0.15).

Negative Correlations: Alcohol use disorders and schizophrenia (-0.75), and alcohol use disorders and anxiety disorders (-0.14).

```
In [13]: import warnings warnings.filterwarnings('ignore')
```

5. Clustering Analysis

```
In [14]:
          import os
          from sklearn.cluster import KMeans
          import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn as sns
          # Set the environment variable to avoid the memory leak warning
          os.environ['OMP_NUM_THREADS'] = 'l'
          # Prepare the data for clustering (use only the latest year)
          data_clustering = data_normalized[data_normalized['Year'] == year_to_compare].drop(columns=['Entity', 'Year'])
          # Fit the K-means model with n_init explicitly set
          kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
          clusters = kmeans.fit_predict(data_clustering)
          # Create a new DataFrame for the subset with cluster labels
          data_clustering_with_clusters = data_normalized[data_normalized['Year'] == year_to_compare].copy()
          data_clustering_with_clusters['Cluster'] = clusters
          # Plot the clusters
          plt.figure(figsize=(14, 8))
          sns.scatterplot(x='Depression (%)', y='Anxiety disorders (%)', hue='Cluster', data=data_clustering_with_clusters,
          plt.title('Clusters of Countries Based on Mental Health Disorders')
          plt.xlabel('Depression (%)')
          plt.ylabel('Anxiety disorders (%)')
          plt.legend(title='Cluster')
          plt.show()
```

