PROJECT OVERVIEW

The COVID-19 pandemic has been one of the most significant global health crises of the modern era, affecting countries worldwide in unprecedented ways. This analysis examines COVID-19 data across multiple countries to understand infection rates, mortality patterns, and vaccination progress. By analyzing this data, we can gain valuable insights into how different countries responded to the pandemic and identify patterns that might inform future public health strategies.

BUSINESS PROBLEM

Health authorities and policymakers need data-driven insights to understand the progression of COVID-19 across different countries. This analysis aims to:

1. Compare infection and mortality rates across selected countries
2. Track vaccination campaign effectiveness
3. Identify patterns in pandemic waves
4. Provide visualizations that clearly communicate pandemic dynamics

OBJECTIVES

1. Clean and prepare COVID-19 data for effective analysis
2. Generate descriptive statistics for key pandemic metrics
3. Create visualizations showing trends across selected countries
4. Analyze vaccination progress and its relationship to case numbers
5. Deliver insights that could inform public health decision-making

In [1]:

```
#importing relevant libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
#load data
df = pd.read_csv('owid-covid-data.csv')
df.head()
```

Out[2]:

	iso_code	continent	location	date	total_cases	new_cases	new_cases_smoothed
0	AFG	Asia	Afghanistan	2020-01-05	0.0	0.0	NaN
1	AFG	Asia	Afghanistan	2020-01-06	0.0	0.0	NaN
2	AFG	Asia	Afghanistan	2020-01-07	0.0	0.0	NaN

3	AFG	Asia	Afghanistan	2020-01-08	0.0	0.0	NaN
4	AFG	Asia	Afghanistan	2020-01-09	0.0	0.0	NaN

5 rows × 67 columns

In [3]:

```
#check for no. of columns and rows
df.shape
```

Out[3]: (429435, 67)

In [4]:

```
# check the columns available
df.columns
```

Out[4]:

```
Index(['iso_code', 'continent', 'location', 'date', 'total_cases', 'new_cases',
       'new_cases_smoothed', 'total_deaths', 'new_deaths',
       'new_deaths_smoothed', 'total_cases_per_million',
       'new_cases_per_million', 'new_cases_smoothed_per_million',
       'total_deaths_per_million', 'new_deaths_per_million',
       'new_deaths_smoothed_per_million', 'reproduction_rate', 'icu_patients',
       'icu_patients_per_million', 'hosp_patients',
       'hosp_patients_per_million', 'weekly_icu_admissions',
       'weekly_icu_admissions_per_million', 'weekly_hosp_admissions',
       'weekly_hosp_admissions_per_million', 'total_tests', 'new_tests',
       'total_tests_per_thousand', 'new_tests_per_thousand',
       'new_tests_smoothed', 'new_tests_smoothed_per_thousand',
       'positive_rate', 'tests_per_case', 'tests_units', 'total_vaccinations',
       'people_vaccinated', 'people_fully_vaccinated', 'total_boosters',
       'new_vaccinations', 'new_vaccinations_smoothed',
       'total_vaccinations_per_hundred', 'people_vaccinated_per_hundred',
       'people_fully_vaccinated_per_hundred', 'total_boosters_per_hundred',
       'new_vaccinations_smoothed_per_million',
       'new_people_vaccinated_smoothed',
       'new_people_vaccinated_smoothed_per_hundred', 'stringency_index',
       'population_density', 'median_age', 'aged_65_older', 'aged_70_older',
       'gdp_per_capita', 'extreme_poverty', 'cardiovasc_death_rate',
       'diabetes_prevalence', 'female_smokers', 'male_smokers',
       'handwashing_facilities', 'hospital_beds_per_thousand',
       'life_expectancy', 'human_development_index', 'population',
       'excess_mortality_cumulative_absolute', 'excess_mortality_cumulative',
       'excess_mortality', 'excess_mortality_cumulative_per_million'],
      dtype='object')
```

In [5]:

```
print(df.isnull().sum())
```

```
iso_code                                         0
continent                                    26525
location                                         0
date                                             0
total_cases                                  17631
                                              ...
population                                       0
```

```
excess_mortality_cumulative_absolute       416024
excess_mortality_cumulative                416024
excess_mortality                           416024
excess_mortality_cumulative_per_million    416024
Length: 67, dtype: int64
```

In [6]:
```
# check for data types
df.dtypes
```

Out[6]:
```
iso_code                                    object
continent                                   object
location                                    object
date                                        object
total_cases                                float64
                                              ...
population                                   int64
excess_mortality_cumulative_absolute       float64
excess_mortality_cumulative                float64
excess_mortality                           float64
excess_mortality_cumulative_per_million    float64
Length: 67, dtype: object
```

In [7]:
```
# basic statistics for numerical columns
print(df.describe())
```

```
        total_cases     new_cases  new_cases_smoothed  total_deaths  \
count  4.118040e+05  4.101590e+05        4.089290e+05  4.118040e+05
mean   7.365292e+06  8.017360e+03        8.041026e+03  8.125957e+04
std    4.477582e+07  2.296649e+05        8.661611e+04  4.411901e+05
min    0.000000e+00  0.000000e+00        0.000000e+00  0.000000e+00
25%    6.280750e+03  0.000000e+00        0.000000e+00  4.300000e+01
50%    6.365300e+04  0.000000e+00        1.200000e+01  7.990000e+02
75%    7.582720e+05  0.000000e+00        3.132860e+02  9.574000e+03
max    7.758668e+08  4.423623e+07        6.319461e+06  7.057132e+06

          new_deaths  new_deaths_smoothed  total_cases_per_million  \
count  410608.000000        409378.000000            411804.000000
mean       71.852139            72.060873            112096.199396
std      1368.322990           513.636567            162240.412419
min         0.000000             0.000000                 0.000000
25%         0.000000             0.000000              1916.100500
50%         0.000000             0.000000             29145.475000
75%         0.000000             3.143000            156770.190000
max    103719.000000         14817.000000            763598.600000

       new_cases_per_million  new_cases_smoothed_per_million  \
count          410159.000000                   408929.000000
mean              122.357074                      122.713844
std              1508.778583                      559.701638
min                 0.000000                        0.000000
25%                 0.000000                        0.000000
50%                 0.000000                        2.794000
75%                 0.000000                       56.253000
max            241758.230000                    34536.890000

       total_deaths_per_million  ...   male_smokers  handwashing_facilities  \
count             411804.000000  ...  243817.000000           161741.000000
mean                 835.514313  ...      33.097723               50.649264
std                 1134.932671  ...      13.853948               31.905375
```

```
min             0.000000  ...       7.700000               1.188000
25%            24.568000  ...      22.600000              20.859000
50%           295.089000  ...      33.100000              49.542000
75%          1283.817000  ...      41.500000              82.502000
max          6601.110000  ...      78.100000             100.000000

       hospital_beds_per_thousand  life_expectancy  human_development_index  \
count               290689.000000    390299.000000            319127.000000
mean                     3.106912        73.702098                 0.722139
std                      2.549205         7.387914                 0.148903
min                      0.100000        53.280000                 0.394000
25%                      1.300000        69.500000                 0.602000
50%                      2.500000        75.050000                 0.740000
75%                      4.210000        79.460000                 0.829000
max                     13.800000        86.750000                 0.957000

         population  excess_mortality_cumulative_absolute  \
count  4.294350e+05                          1.341100e+04
mean   1.520336e+08                          5.604765e+04
std    6.975408e+08                          1.568691e+05
min    4.700000e+01                         -3.772610e+04
25%    5.237980e+05                          1.765000e+02
50%    6.336393e+06                          6.815199e+03
75%    3.296952e+07                          3.912804e+04
max    7.975105e+09                          1.349776e+06

       excess_mortality_cumulative  excess_mortality  \
count                 13411.000000      13411.000000
mean                      9.766431         10.925353
std                      12.040658         24.560706
min                     -44.230000        -95.920000
25%                       2.060000         -1.500000
50%                       8.130000          5.660000
75%                      15.160000         15.575000
max                      78.080000        378.220000

       excess_mortality_cumulative_per_million
count                             13411.000000
mean                               1772.666400
std                                1991.892769
min                               -2936.453100
25%                                116.872242
50%                               1270.801400
75%                               2883.024150
max                              10293.515000

[8 rows x 62 columns]
```

In [8]:

```
#Data Cleaning
# Create a copy of the dataframe to avoid modifying the original
data= df.copy()
data.head()
```

Out[8]:

	iso_code	continent	location	date	total_cases	new_cases	new_cases_smoothed
0	AFG	Asia	Afghanistan	2020-01-05	0.0	0.0	NaN
1	AFG	Asia	Afghanistan	2020-	0.0	0.0	NaN

				01-06			
2	AFG	Asia	Afghanistan	2020-01-07	0.0	0.0	NaN
3	AFG	Asia	Afghanistan	2020-01-08	0.0	0.0	NaN
4	AFG	Asia	Afghanistan	2020-01-09	0.0	0.0	NaN

5 rows × 67 columns

In [9]:

```
#convert date column to datetime
data['date'] =pd.to_datetime(data['date'])
```

In [10]:

```
selected_columns = ['date', 'country', 'cases_total', 'cases_new',
                    'deaths_total', 'deaths_new',
                    'vaccinations_total', 'vaccinated_partial', 'vaccinated_full
```

In [11]:

```
clean_data = data.rename(columns={
    'location': 'country',
    'total_cases': 'cases_total',
    'new_cases': 'cases_new',
    'total_deaths': 'deaths_total',
    'new_deaths': 'deaths_new',
    'total_vaccinations': 'vaccinations_total',
    'people_vaccinated': 'vaccinated_partial',
    'people_fully_vaccinated': 'vaccinated_full'
})
```

In [12]:

```
selected_columns = ['date', 'country', 'cases_total', 'cases_new',
                    'deaths_total', 'deaths_new',
                    'vaccinations_total', 'vaccinated_partial', 'vaccinated_full
df1 = clean_data[selected_columns]
```

In [13]:

```
df1.head()
```

Out[13]:

	date	country	cases_total	cases_new	deaths_total	deaths_new	vaccinations_tota
0	2020-01-05	Afghanistan	0.0	0.0	0.0	0.0	Nal
1	2020-01-06	Afghanistan	0.0	0.0	0.0	0.0	Nal
2	2020-01-07	Afghanistan	0.0	0.0	0.0	0.0	Nal
3	2020-01-08	Afghanistan	0.0	0.0	0.0	0.0	Nal

4	2020-01-09	Afghanistan	0.0	0.0	0.0	0.0	NaN

In [14]:

```
df1.shape
```

Out[14]: (429435, 11)

In [15]:

```
#Handling Missing Values in Critical Columns
print(df1.isnull().sum())
```

```
date                      0
country                   0
cases_total           17631
cases_new             19276
deaths_total          17631
deaths_new            18827
vaccinations_total   344018
vaccinated_partial   348303
vaccinated_full      351374
population                0
iso_code                  0
dtype: int64
```

In [16]:

```
critical_columns = ['cases_total', 'deaths_total', 'cases_new', 'deaths_new']

# Drop rows where date is missing (if any)
df1 = df1.dropna(subset=['date'])
```

In [17]:

```
df1[critical_columns] = df1.groupby('country')[critical_columns].ffill()

# For any remaining NaN values at the beginning of a series, fill with 0
df1[critical_columns] = df1[critical_columns].fillna(0)

# Check if we've addressed the missing values
print("Missing values in critical columns after cleaning:")
df1[critical_columns].isnull().sum()
```

```
Missing values in critical columns after cleaning:
```

Out[17]:

```
cases_total     0
deaths_total    0
cases_new       0
deaths_new      0
dtype: int64
```

In [18]:

```
# Let's also handle vaccination data
vaccination_columns = ['vaccinations_total', 'vaccinated_partial', 'vaccinated_f

# First, check missing values in vaccination columns
print("Missing values in vaccination columns before cleaning:")
df1[vaccination_columns].isnull().sum()

# Forward fill the vaccination data by country
```

```
df1[vaccination_columns] = df1.groupby('country')[vaccination_columns].ffill()

# For any remaining NaN values, let's check how many we have
print("Missing values in vaccination columns after forward fill:")
df1[vaccination_columns].isnull().sum()

# Since vaccinations started later in the pandemic, early dates will naturally h
# Let's replace those with 0
df1[vaccination_columns] = df1[vaccination_columns].fillna(0)
```

```
Missing values in vaccination columns before cleaning:
Missing values in vaccination columns after forward fill:
```

In [19]:

```
#  cleaning results
print("Final missing values in vaccination columns:")
df1[vaccination_columns].isnull().sum()
```

```
Final missing values in vaccination columns:
```

Out[19]:

```
vaccinations_total    0
vaccinated_partial    0
vaccinated_full       0
dtype: int64
```

In [20]:

```
# Check data types after cleaning
df1.dtypes
```

Out[20]:

```
date                  datetime64[ns]
country                       object
cases_total                  float64
cases_new                    float64
deaths_total                 float64
deaths_new                   float64
vaccinations_total           float64
vaccinated_partial           float64
vaccinated_full              float64
population                     int64
iso_code                      object
dtype: object
```

In [21]:

```
df1.head()
```

Out[21]:

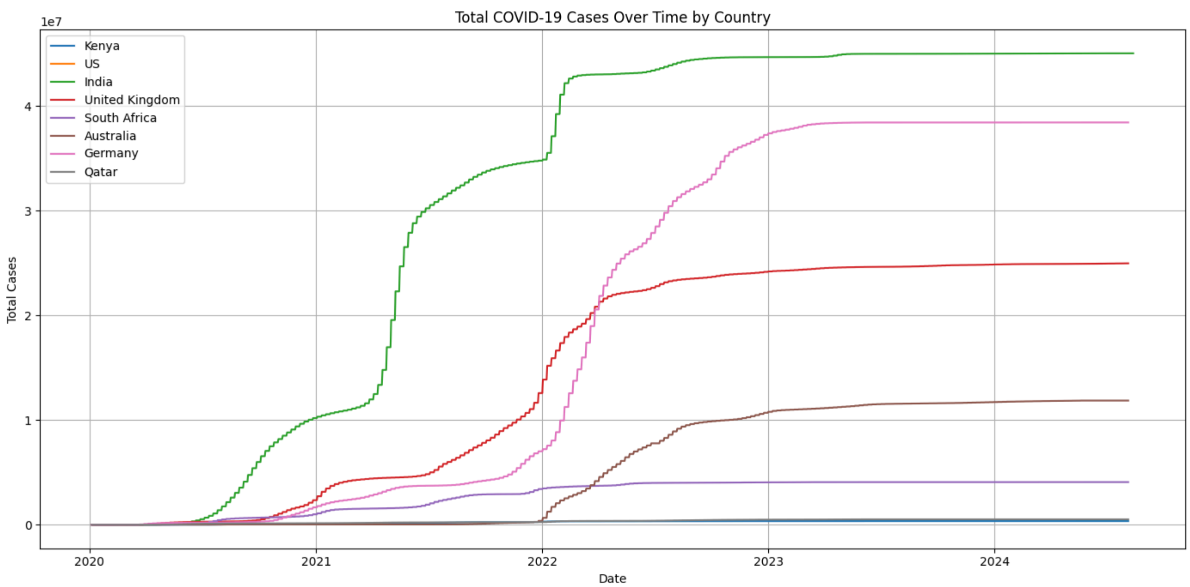
	date	country	cases_total	cases_new	deaths_total	deaths_new	vaccinations_tota
0	2020-01-05	Afghanistan	0.0	0.0	0.0	0.0	0.(
1	2020-01-06	Afghanistan	0.0	0.0	0.0	0.0	0.(
2	2020-01-07	Afghanistan	0.0	0.0	0.0	0.0	0.(
3	2020-01-08	Afghanistan	0.0	0.0	0.0	0.0	0.(
4	2020-01-09	Afghanistan	0.0	0.0	0.0	0.0	0.(

In [22]:

```
 #Exploratory Data Analysis (EDA)
countries= ['Kenya','US', 'India','United Kingdom','South Africa','Australia','G
```

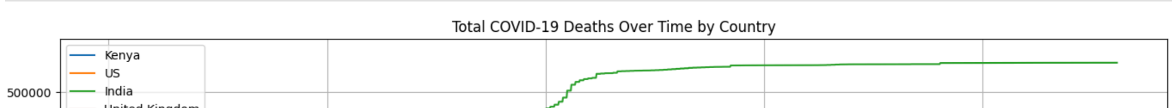
In [23]:

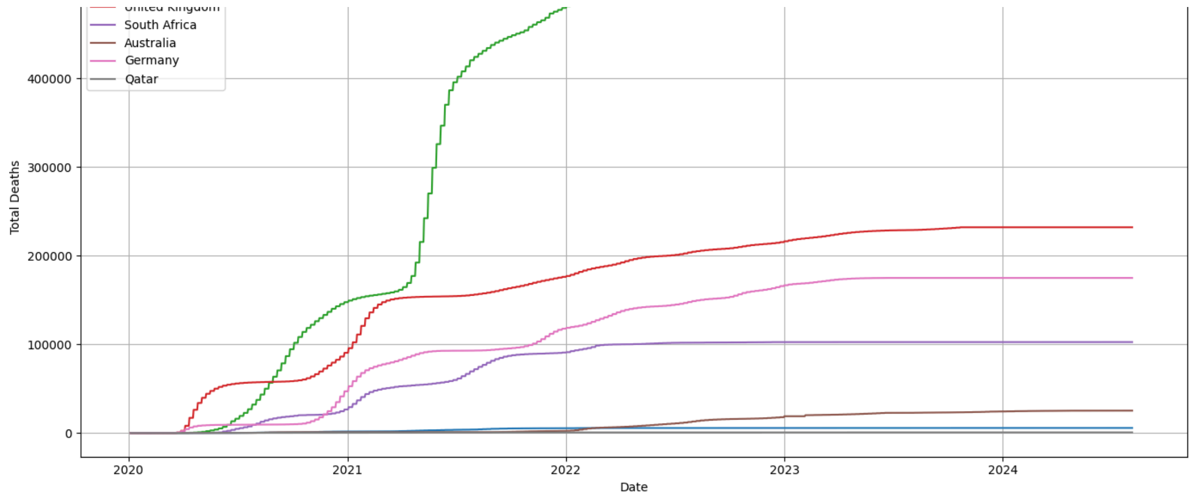
```
plt.figure(figsize=(14, 7))

for country in countries:
    df_country = df1[df1['country'] == country]
    plt.plot(df_country['date'], df_country['cases_total'], label=country)

plt.xlabel('Date')
plt.ylabel('Total Cases')
plt.title('Total COVID-19 Cases Over Time by Country')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [24]:

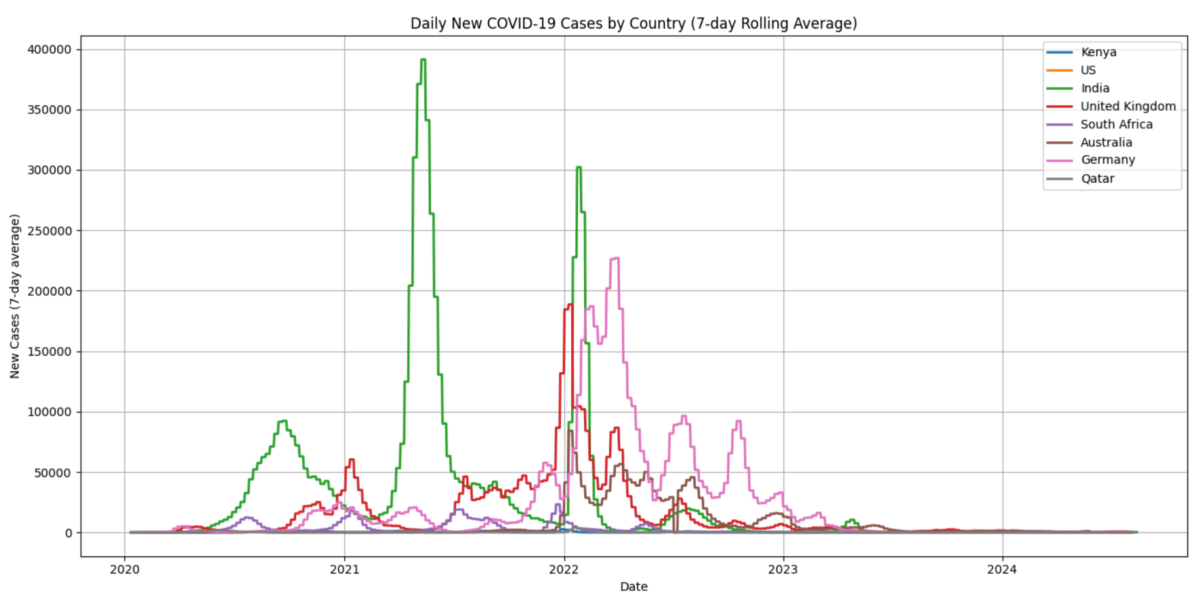
```
plt.figure(figsize=(14, 7))

for country in countries:
    df_country = df1[df1['country'] == country]
    plt.plot(df_country['date'], df_country['deaths_total'], label=country)

plt.xlabel('Date')
plt.ylabel('Total Deaths')
plt.title('Total COVID-19 Deaths Over Time by Country')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```





In [25]:

```python
plt.figure(figsize=(14, 7))

for country in countries:
    df_country = df1[df1['country'] == country]
    rolling_avg = df_country['cases_new'].rolling(7).mean()
    plt.plot(df_country['date'], rolling_avg, label=country, linewidth=2)

plt.xlabel('Date')
plt.ylabel('New Cases (7-day average)')
plt.title('Daily New COVID-19 Cases by Country (7-day Rolling Average)')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



Interpretation:

India experienced the most dramatic surge, particularly during mid-2021, reflecting its catastrophic second wave. The United States shows multiple well-defined waves, indicating repeated spikes in infections across different periods. Countries like Kenya, Qatar, and Australia had relatively lower peaks, though still experienced noticeable wave patterns. This chart highlights both the timing and intensity of COVID-19 outbreaks, showing how the pandemic evolved differently across regions.

In [26]:

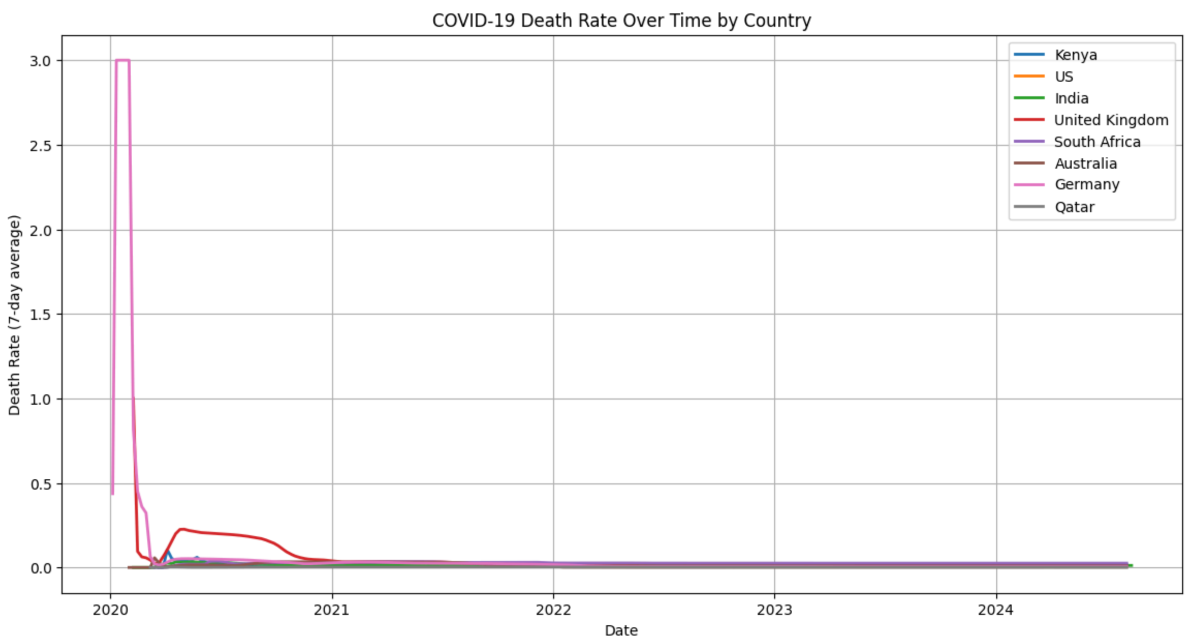
```
df1['death_rate'] = df1['deaths_total'] / df1['cases_total']
```

In [27]:

```
df1['death_rate_smoothed'] = df1['death_rate'].rolling(7).mean()
```

In [28]:

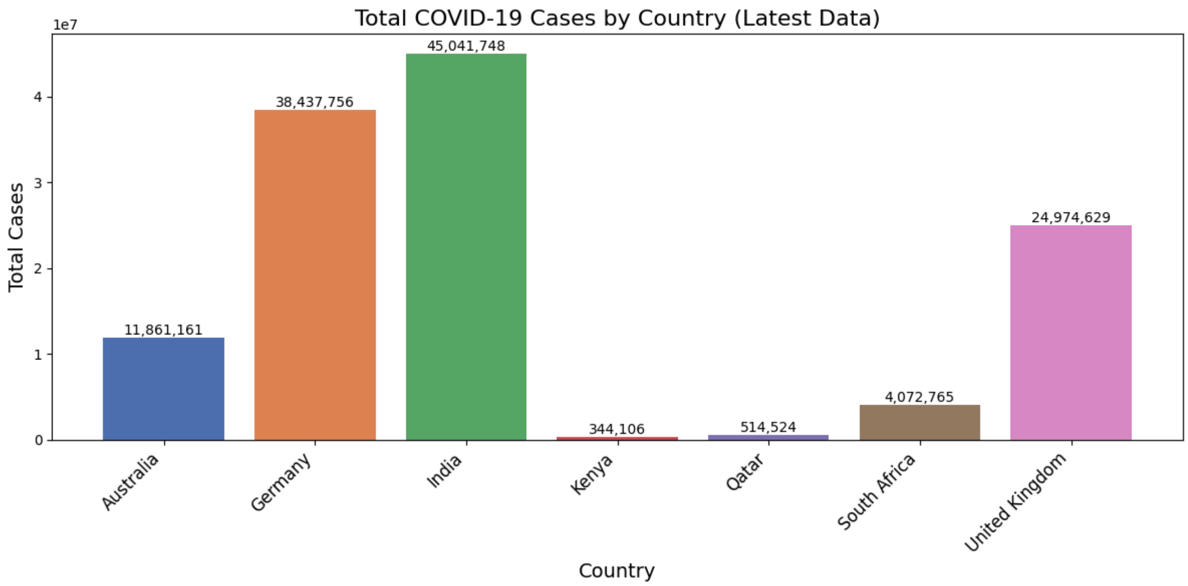
```
plt.figure(figsize=(14, 7))

for country in countries:
    df_country = df1[df1['country'] == country]
    plt.plot(df_country['date'], df_country['death_rate_smoothed'], label=countr

plt.xlabel('Date')
plt.ylabel('Death Rate (7-day average)')
plt.title('COVID-19 Death Rate Over Time by Country')
plt.legend()
plt.grid(True)
#plt.tight_layout()
plt.show()
```



In [29]:

```
# Get the latest data for each country
latest_data = df1[df1['country'].isin(countries)].groupby('country').last().rese

# Create bar chart for total cases
plt.figure(figsize=(12, 6))
bars = plt.bar(latest_data['country'], latest_data['cases_total'], color=sns.col
plt.title('Total COVID-19 Cases by Country (Latest Data)', fontsize=16)
plt.xlabel('Country', fontsize=14)
plt.ylabel('Total Cases', fontsize=14)
plt.xticks(rotation=45, ha="right", fontsize=12)  # Rotate x-axis labels for bet

# Add value labels on top of bars
for bar in bars:
    height = bar.get_height()
```

```
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height,
             f'{int(height):,}',
             ha='center', va='bottom', fontsize=10)

plt.tight_layout()
plt.show()
```



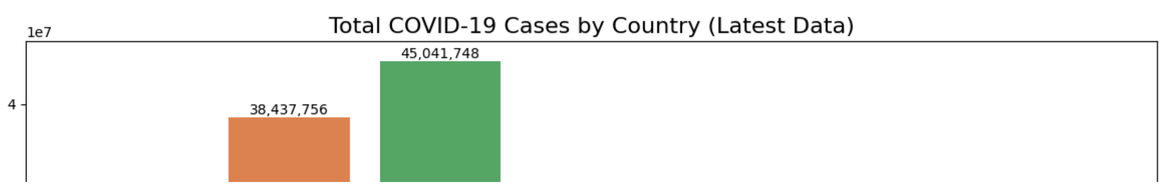
Interpretation:

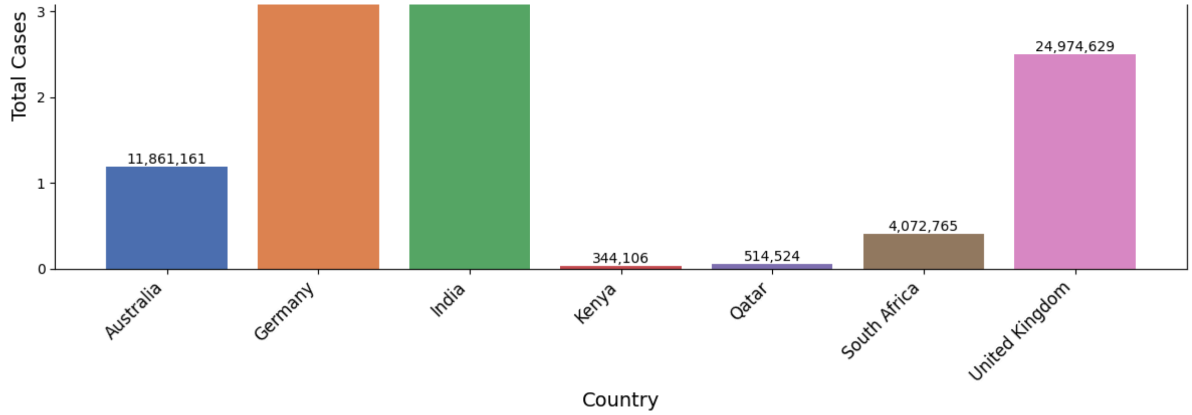
This bar chart compares the total number of COVID-19 cases for Kenya, US, India, United Kingdom, South Africa, Australia, Germany, and Qatar, using the most recent data available. The height of each bar represents the total cases for that country, allowing for a direct visual comparison of the pandemic's impact. It's important to consider that this chart displays absolute case numbers, and differences in population size between countries should be taken into account for a more complete understanding.

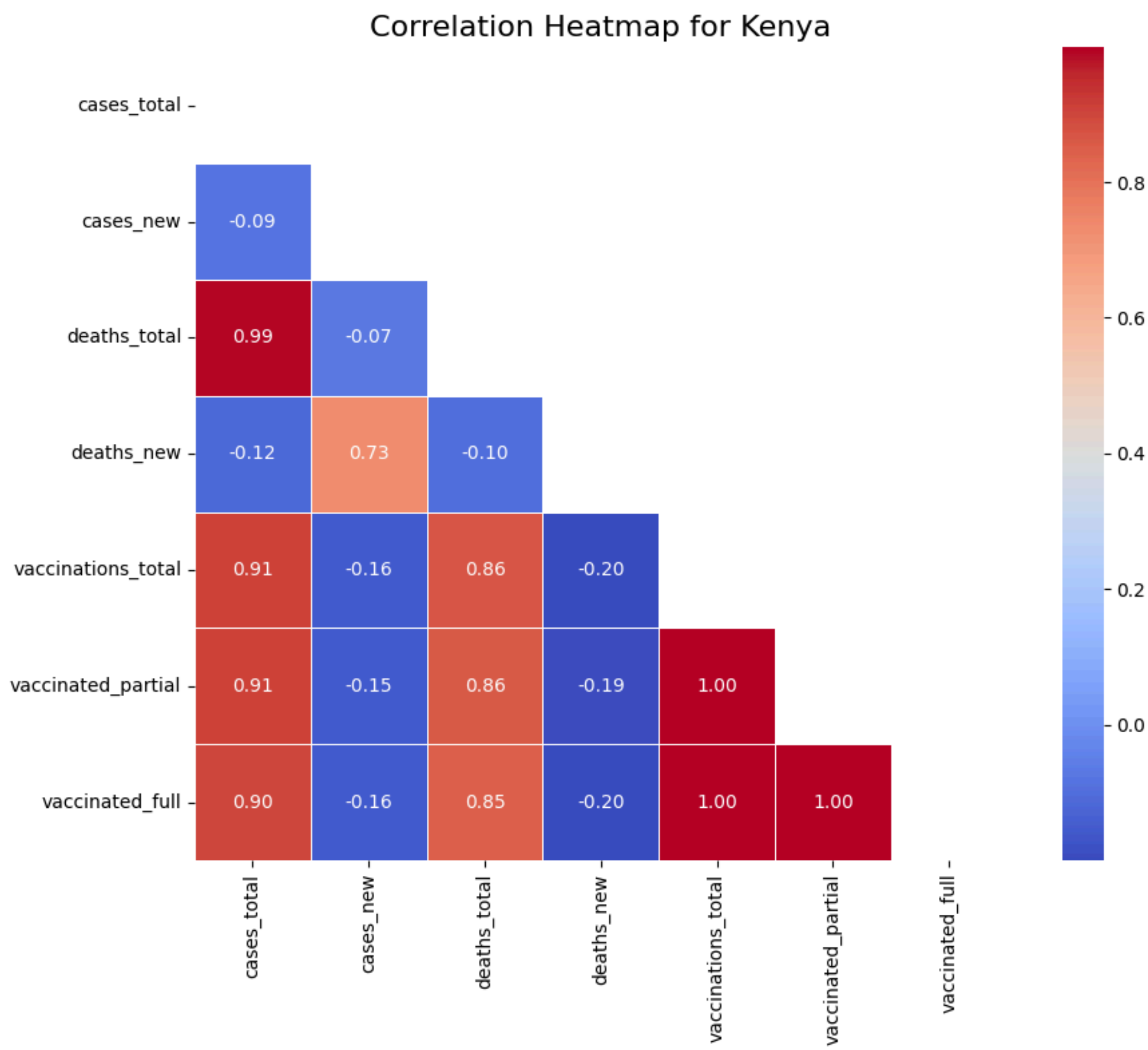
In [30]:

```
# Get the latest data for each country
latest_data = df1[df1['country'].isin(countries)].groupby('country').last().rese
```

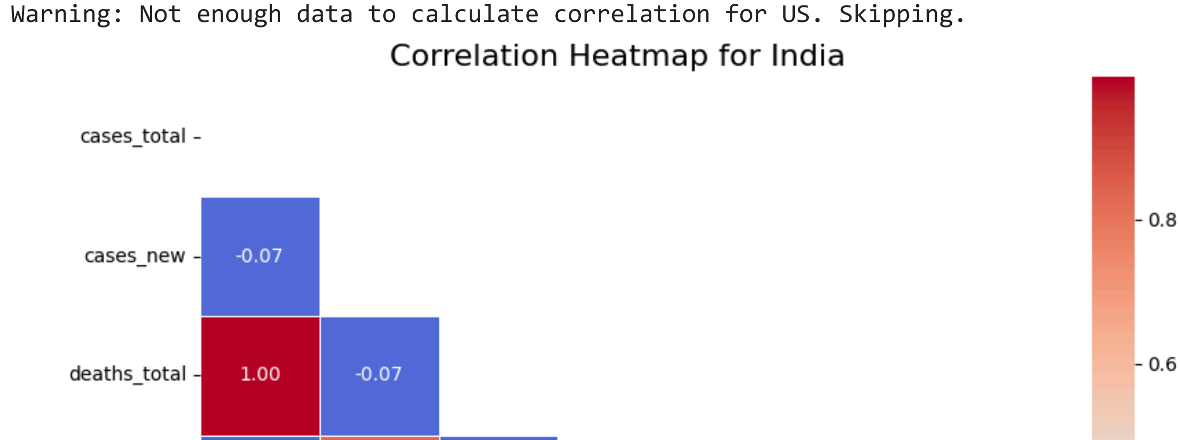
```python
# Create bar chart for total cases
plt.figure(figsize=(12, 6))
bars = plt.bar(latest_data['country'], latest_data['cases_total'], color=sns.col
plt.title('Total COVID-19 Cases by Country (Latest Data)', fontsize=16)
plt.xlabel('Country', fontsize=14)
plt.ylabel('Total Cases', fontsize=14)
plt.xticks(rotation=45, ha="right", fontsize=12)  # Rotate x-axis labels for bet

# Add value labels on top of bars
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height,
             f'{int(height):,}',
             ha='center', va='bottom', fontsize=10)

plt.tight_layout()
plt.show()

### Interpretation:
#This bar chart compares the total number of COVID-19 cases for Kenya, US, India

# Correlation Heatmap for Key Metrics
# Select numerical columns for correlation analysis
numeric_cols = ['cases_total', 'cases_new', 'deaths_total', 'deaths_new',
                 'vaccinations_total', 'vaccinated_partial','vaccinated_full']

# Create correlation matrices for each country
for country in countries:
    country_data = df1[df1['country'] == country][numeric_cols]

    # Calculate correlation
    # Check if country_data is empty or contains only NaNs
    if country_data.empty or country_data.isnull().all().all():
        print(f"Warning: Not enough data to calculate correlation for {country}.
        continue  # Skip to the next country

    corr = country_data.corr()

    # Check if the correlation matrix is all NaNs
    if corr.isnull().all().all():
        print(f"Warning: Correlation matrix for {country} is all NaNs. Skipping
        continue

    # Plot heatmap
    plt.figure(figsize=(10, 8))
    mask = np.triu(np.ones_like(corr, dtype=bool))
    try:
        sns.heatmap(corr, mask=mask, cmap='coolwarm', annot=True, fmt='.2f', squ
        plt.title(f'Correlation Heatmap for {country}', fontsize=16)
        plt.tight_layout()
        plt.show()
    except ValueError as e:
        print(f"Warning: Cannot plot heatmap for {country} due to ValueError: {e
```

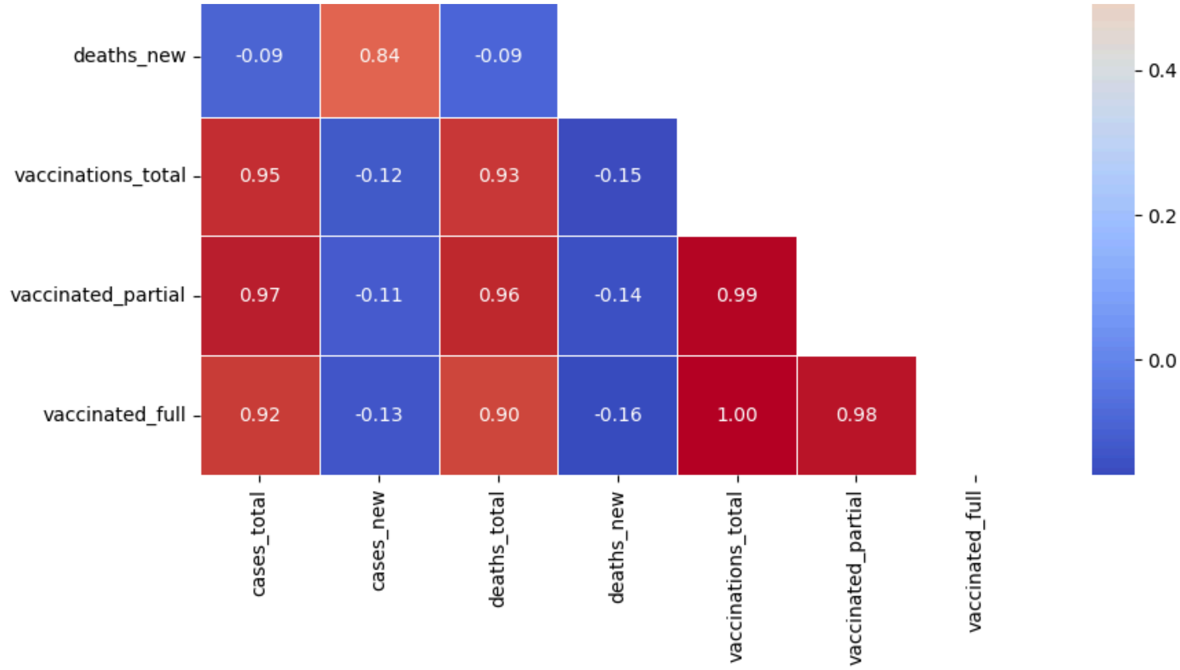




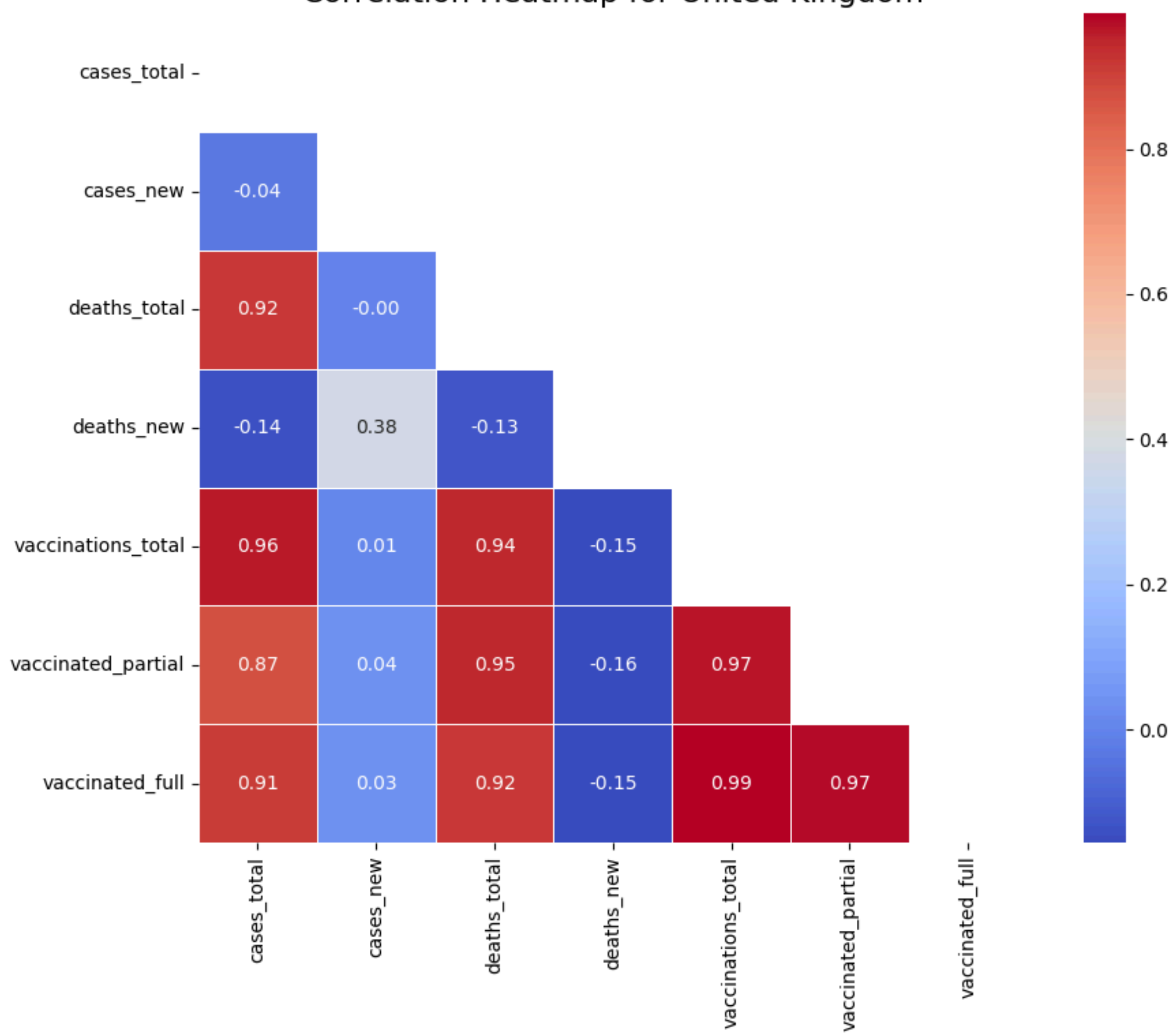



```
Warning: Not enough data to calculate correlation for US. Skipping.
```

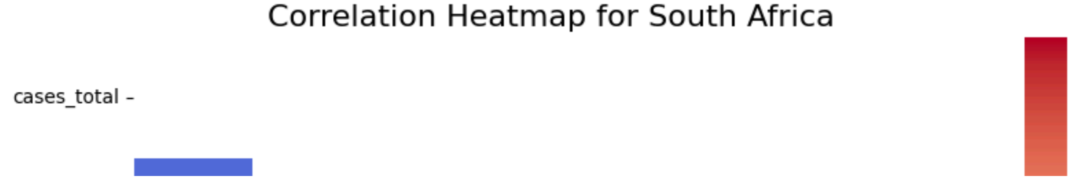


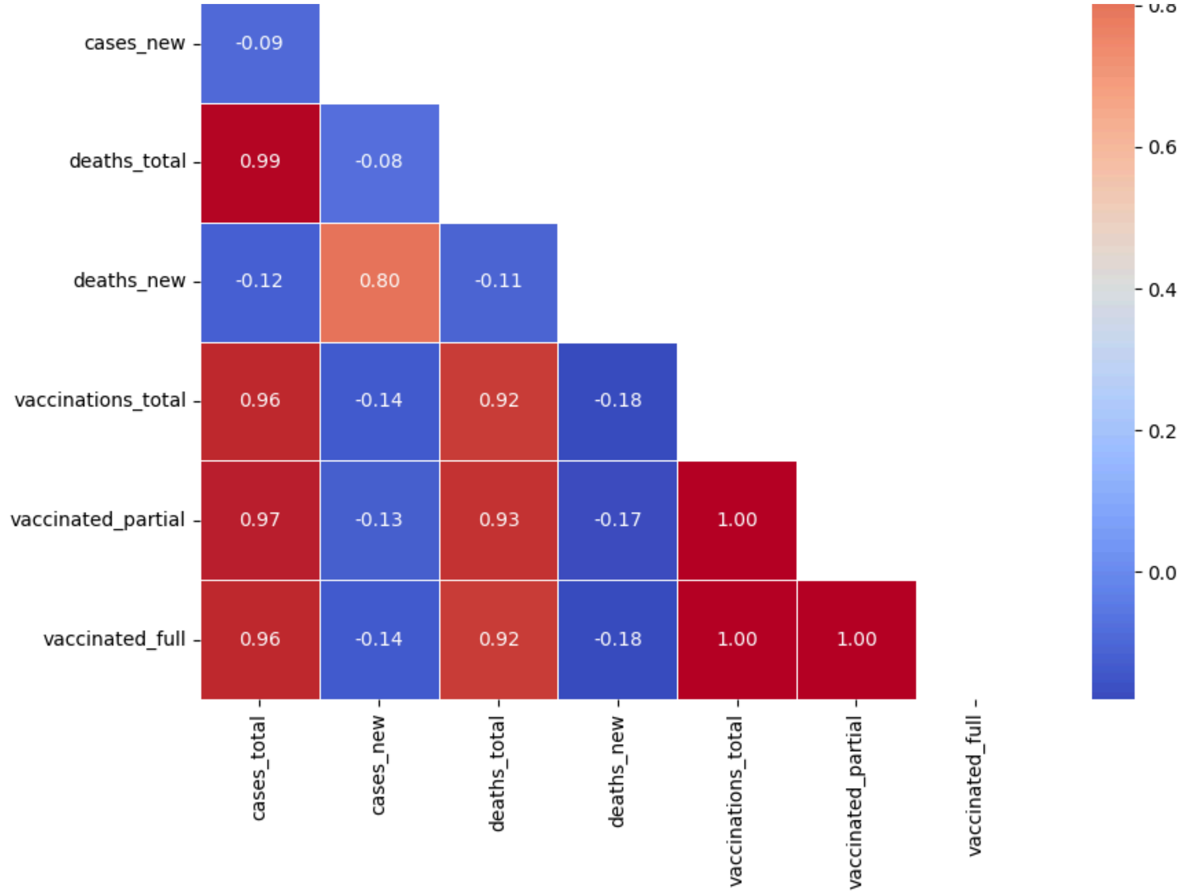


Correlation Heatmap for United Kingdom

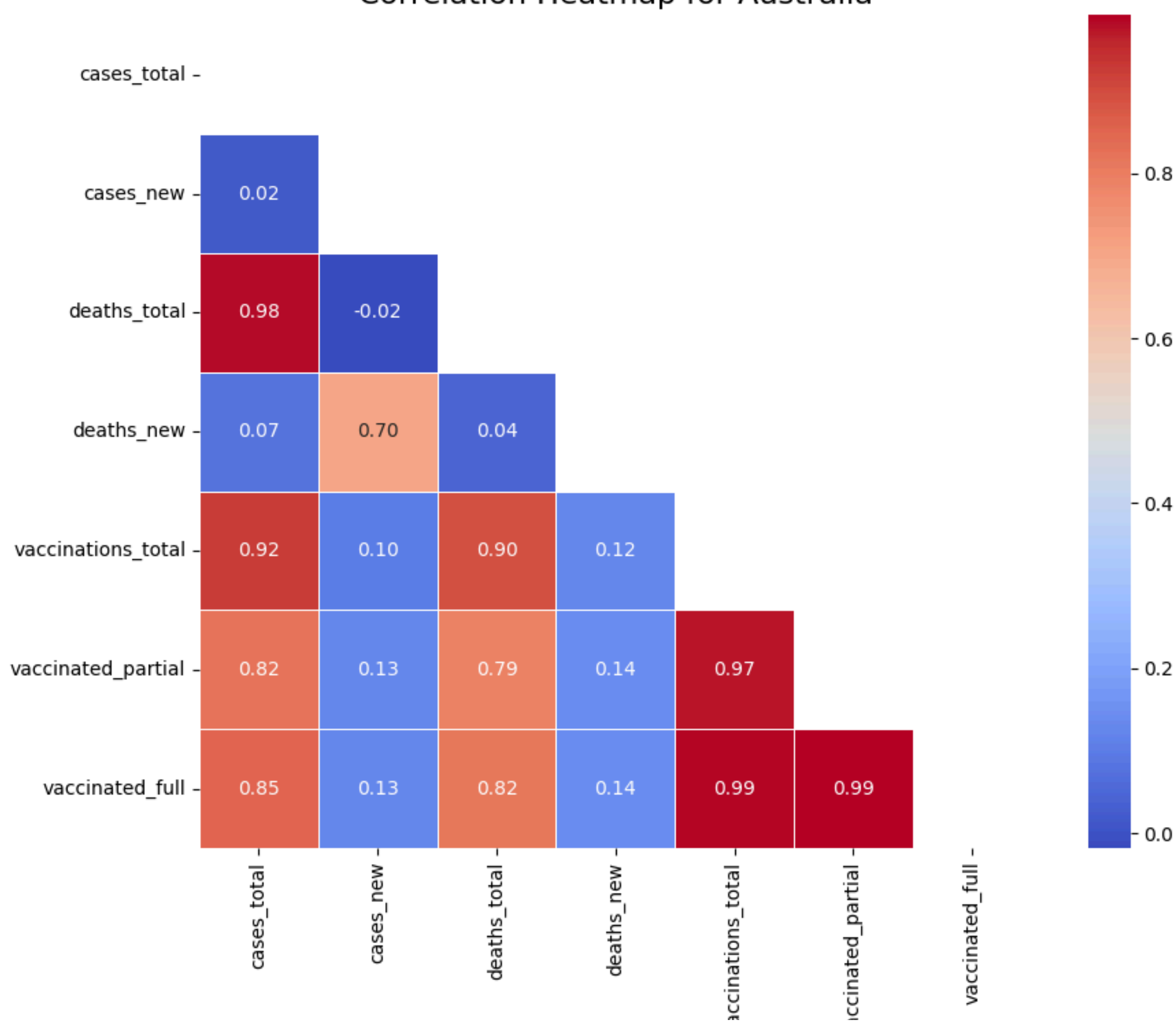


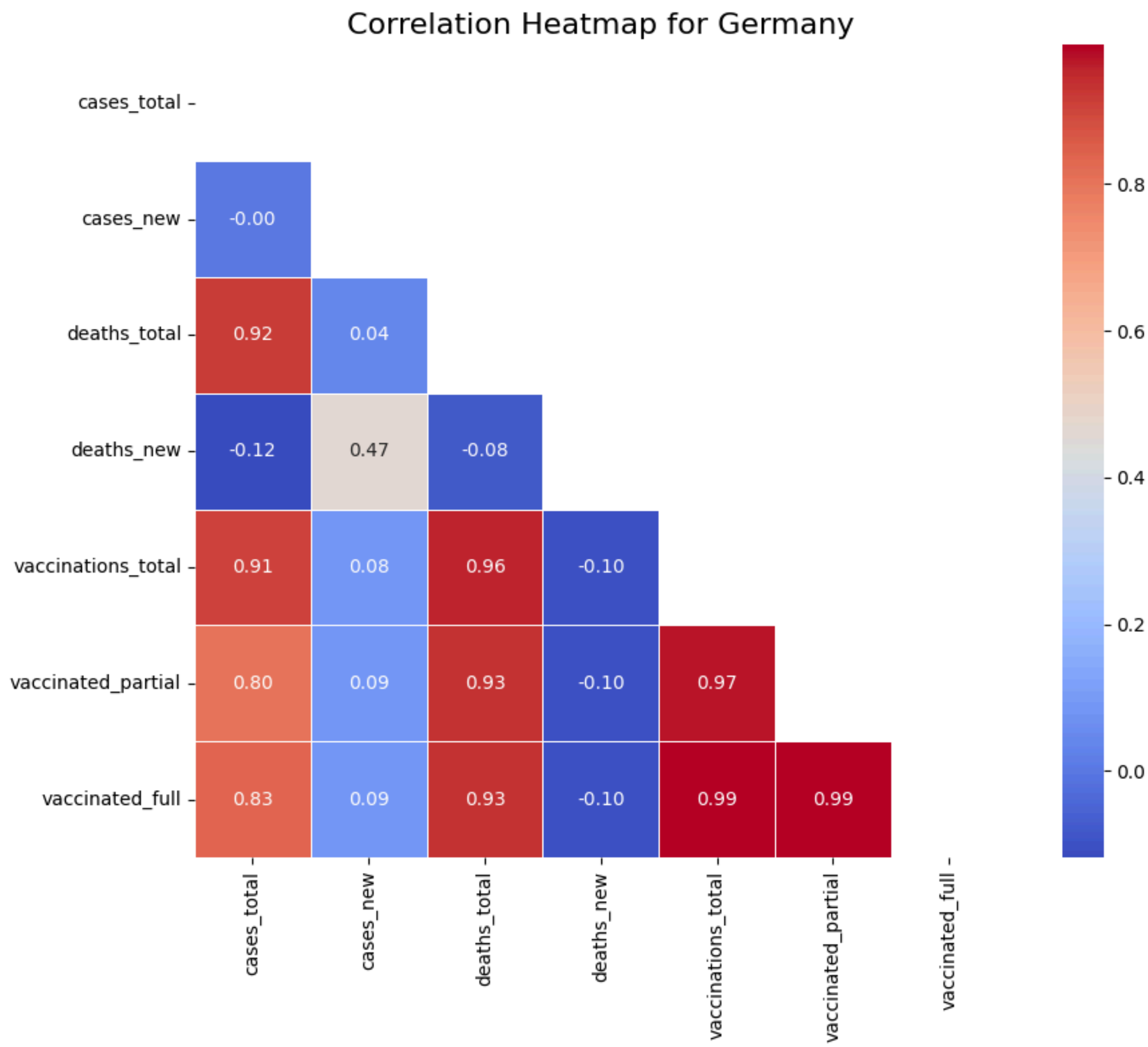
Correlation Heatmap for South Africa

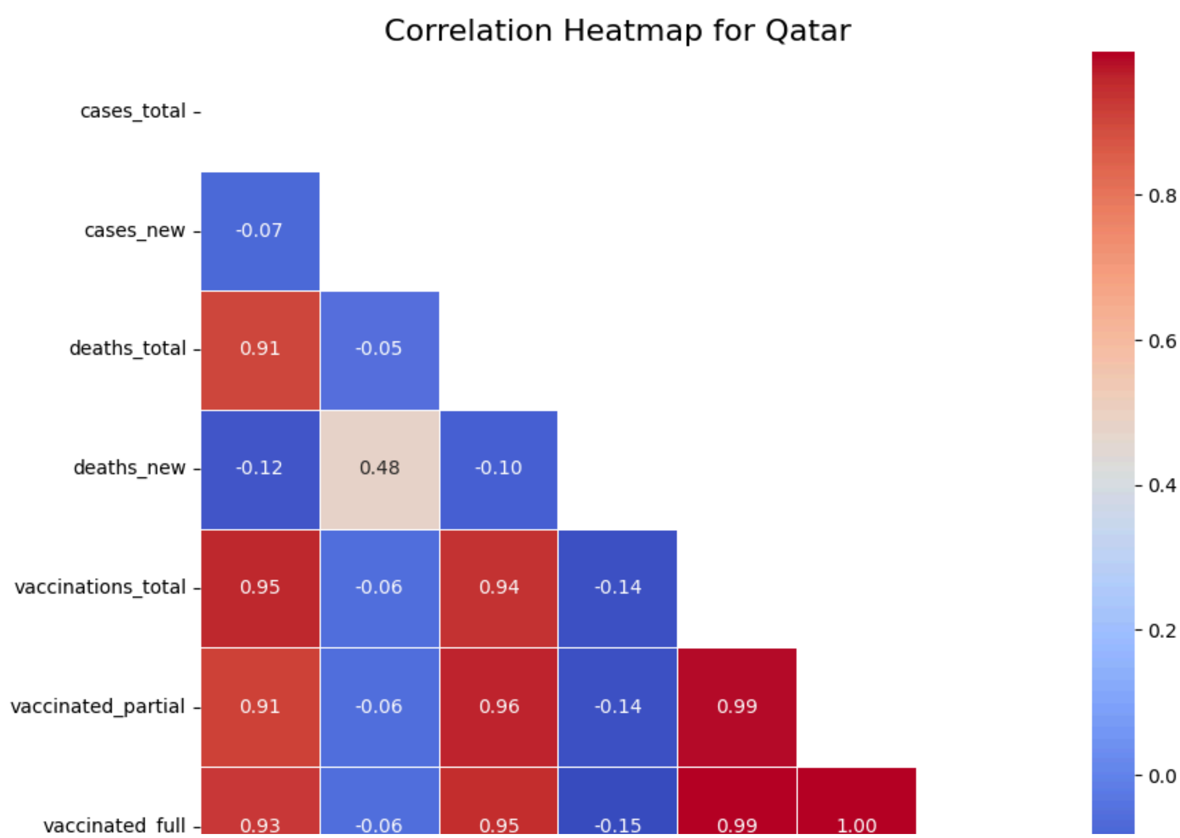


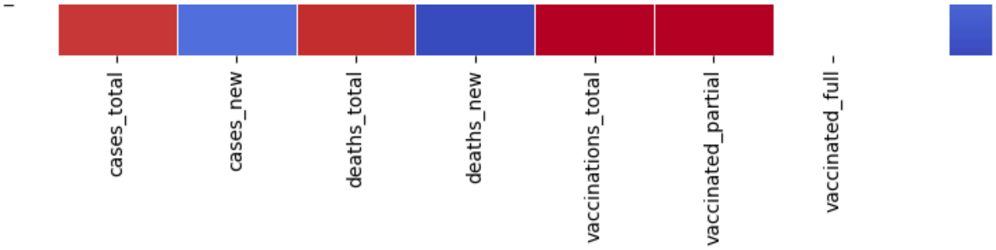


Correlation Heatmap for Australia



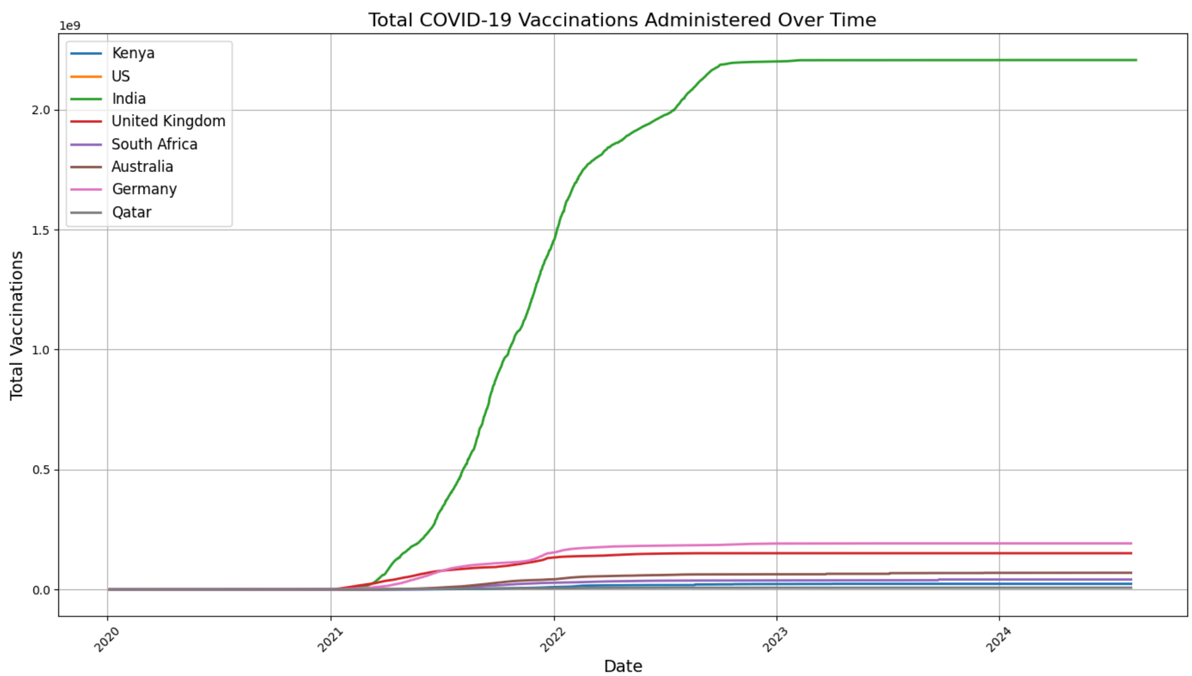

Correlation Heatmap for Germany
cases_total
cases_new
deaths_total
deaths_new
vaccinations_total
vaccinated_partial
vaccinated_full
-0.00
0.92
0.04
-0.12
0.47
-0.08
0.91
0.08
0.96
-0.10
0.80
0.09
0.93
-0.10
0.97
0.83
0.09
0.93
-0.10
0.99
0.99
0.8
0.6
0.4
0.2
0.0


Correlation Heatmap for Qatar
cases_total
cases_new
deaths_total
deaths_new
vaccinations_total
vaccinated_partial
vaccinated_full
-0.07
0.91
-0.05
-0.12
0.48
-0.10
0.95
-0.06
0.94
-0.14
0.91
-0.06
0.96
-0.14
0.99
0.93
-0.06
0.95
-0.15
0.99
1.00
0.8
0.6
0.4
0.2
0.0



In [31]:

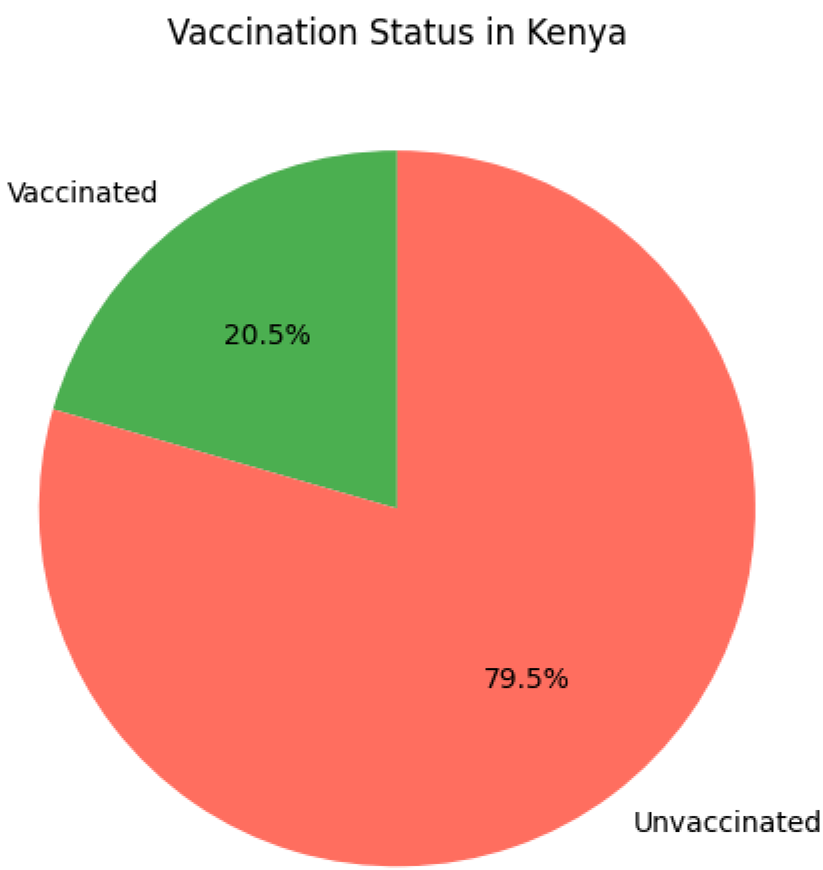
```
#Vaccination Analysis
### 4.1 Total Vaccinations Over Time

plt.figure(figsize=(14, 8))
for country in countries:
    country_data = df1[df1['country'] == country]
    plt.plot(country_data['date'], country_data['vaccinations_total'], label=cou

plt.title('Total COVID-19 Vaccinations Administered Over Time', fontsize=16)
plt.xlabel('Date', fontsize=14)
plt.ylabel('Total Vaccinations', fontsize=14)
plt.legend(fontsize=12)
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



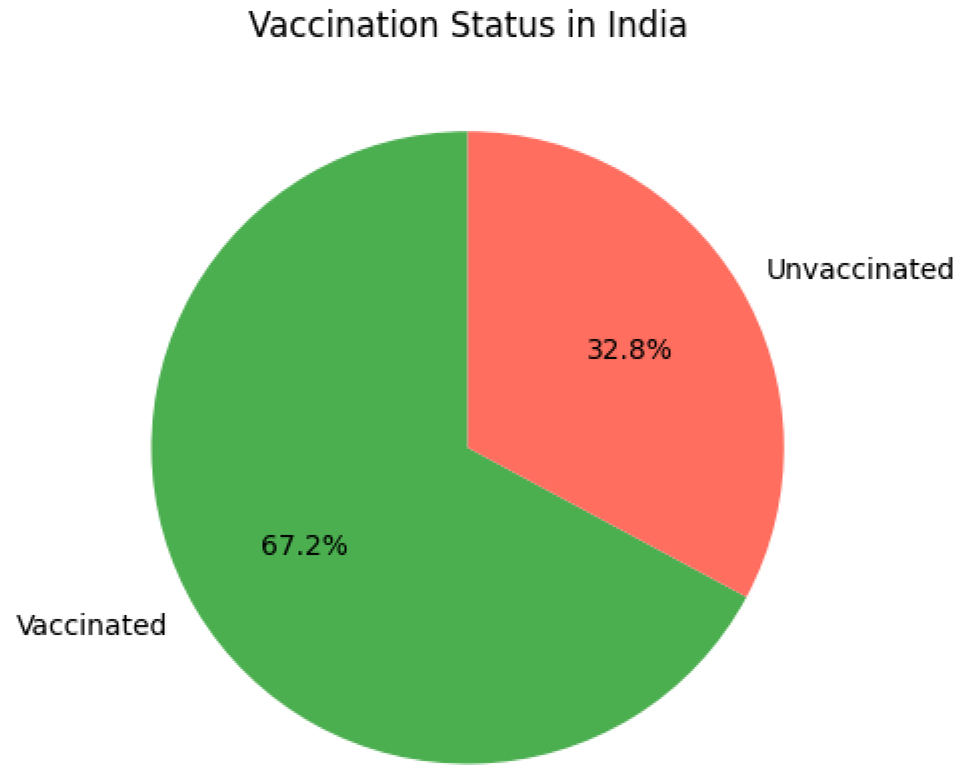
In [32]:

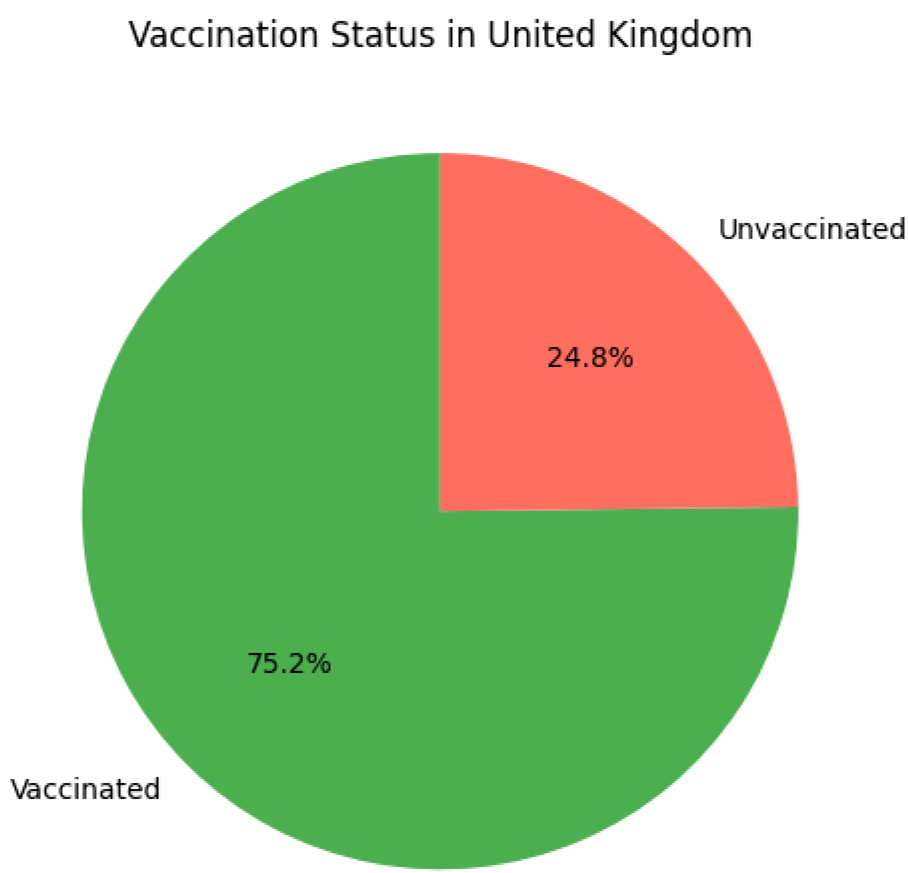
```
for country in countries:
    df_country = df1[df1['country'] == country].sort_values('date')

    if df_country.empty:
        print(f"No data for {country}")
        continue

    latest = df_country.iloc[-1]
    vaccinated = latest['vaccinated_full']
    population = latest['population']
```

```
    # Validate inputs
    if pd.isna(vaccinated) or pd.isna(population):
        print(f"Missing data for {country}")
        continue
    if population <= 0:
        print(f"Invalid population for {country}")
        continue

    vaccinated = min(vaccinated, population)  # Cap vaccinated at population
    unvaccinated = population - vaccinated

    if vaccinated < 0 or unvaccinated < 0:
        print(f"Negative values after cleanup for {country}")
        continue

    # Plot pie chart
    plt.figure(figsize=(5, 5))
    plt.pie(
        [vaccinated, unvaccinated],
        labels=['Vaccinated', 'Unvaccinated'],
        autopct='%1.1f%%',
        startangle=90,
        colors=['#4CAF50', '#FF6F61']
    )
    plt.title(f'Vaccination Status in {country}')
    plt.tight_layout()
    plt.show()
```

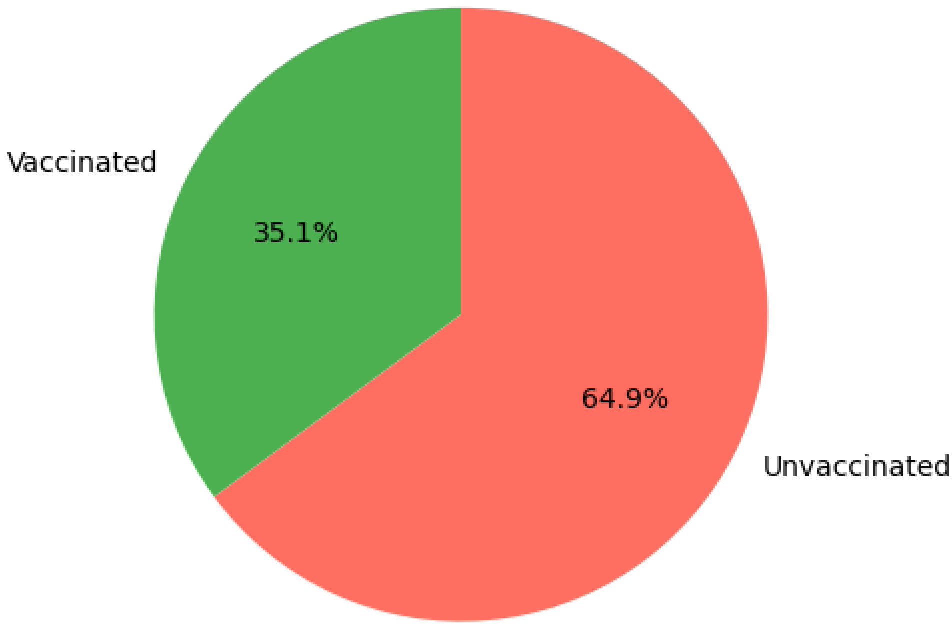


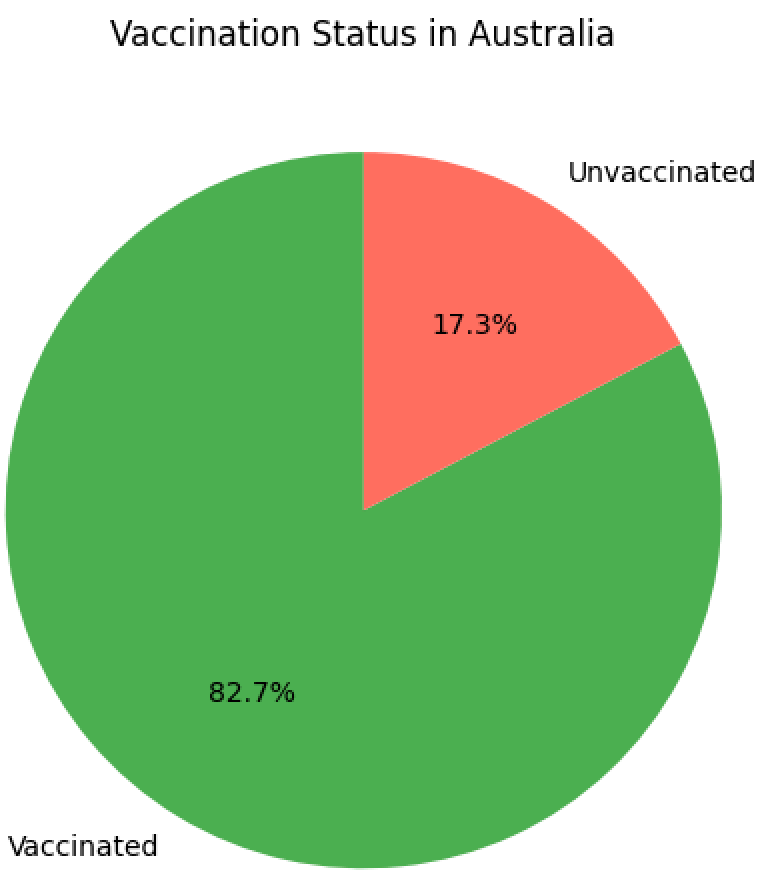

```
No data for US
```

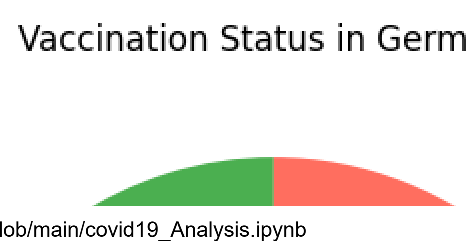


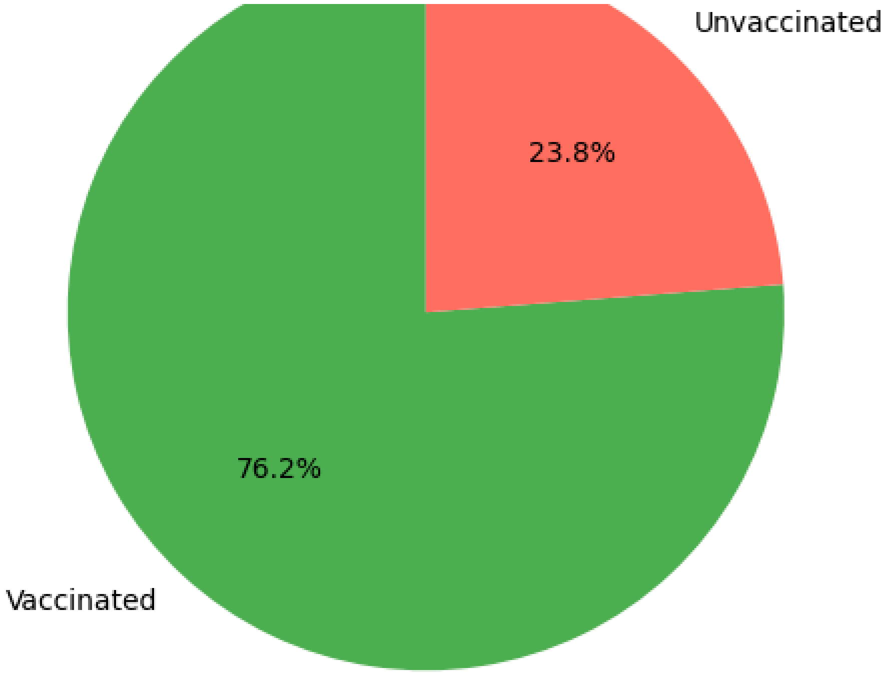


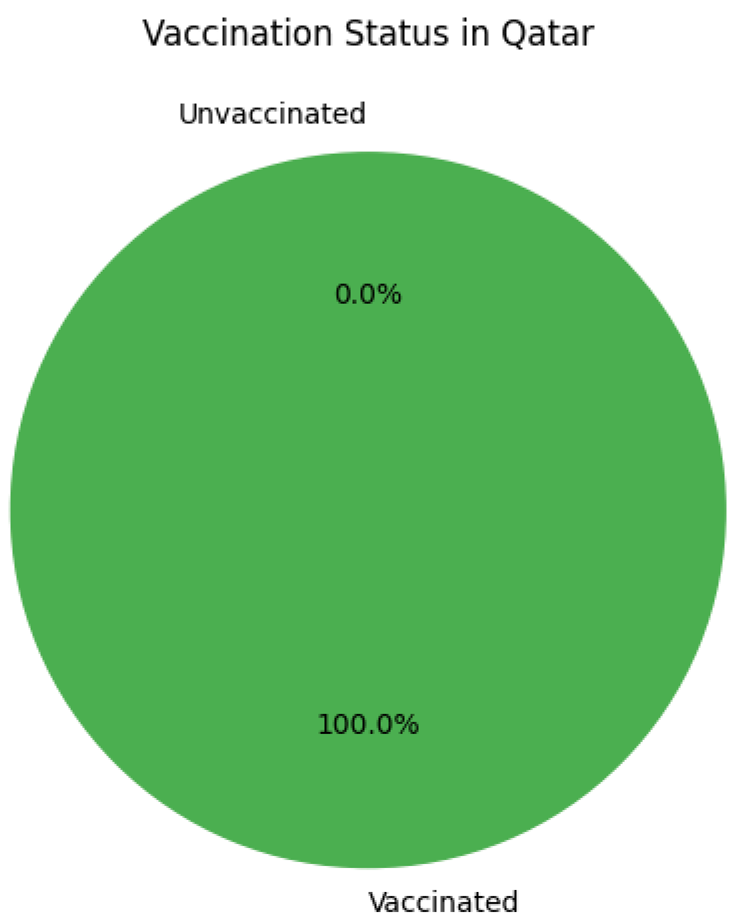
Vaccination Status in South Africa


Vaccinated
35.1%
64.9%
Unvaccinated


Vaccination Status in Australia
Unvaccinated
17.3%
82.7%
Vaccinated


Vaccination Status in Germany



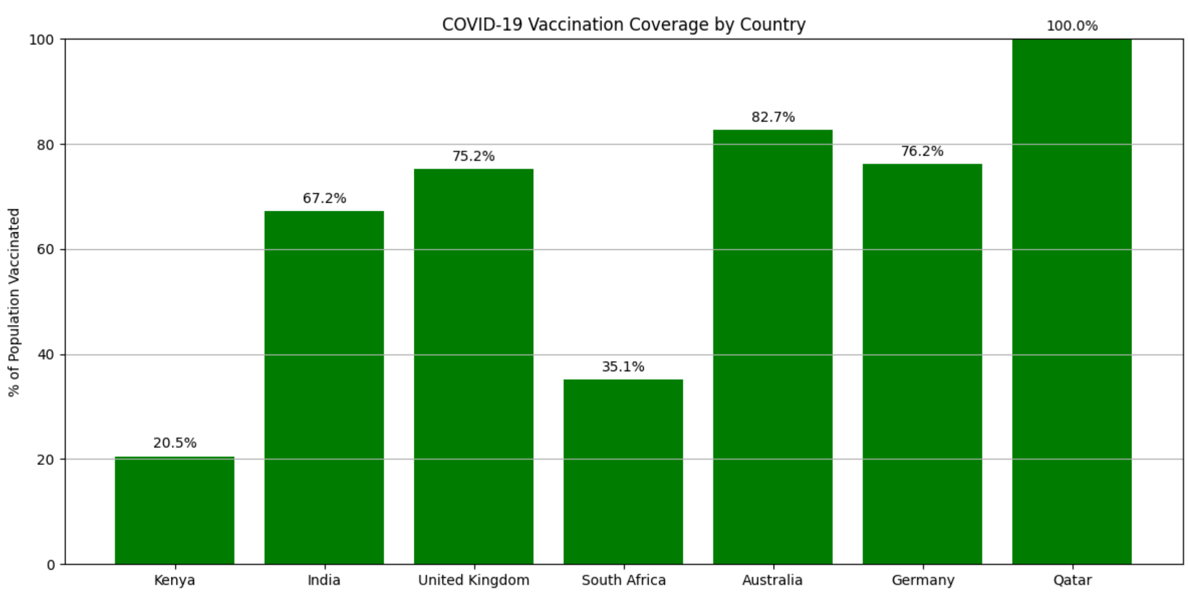


In [33]:

```
# Store vaccination % data
vaccination_data = []

for country in countries:
```

```
    df_country = dfi[dfi['country'] == country].sort_values('date')

    if df_country.empty:
        print(f"No data for {country}")
        continue

    latest = df_country.iloc[-1]
    vaccinated = latest['vaccinated_full']
    population = latest['population']

    # Skip if data is missing or invalid
    if pd.isna(vaccinated) or pd.isna(population) or population == 0:
        print(f"Invalid or missing data for {country}")
        continue

    pct_vaccinated = min(vaccinated / population, 1.0) * 100  # Cap at 100%
    vaccination_data.append((country, pct_vaccinated))

# Unpack data
countries_cleaned, percentages = zip(*vaccination_data)

# Plot bar chart
plt.figure(figsize=(12, 6))
bars = plt.bar(countries_cleaned, percentages, color='green')
plt.ylabel('% of Population Vaccinated')
plt.title('COVID-19 Vaccination Coverage by Country')
plt.ylim(0, 100)
plt.grid(axis='y')

# Add data labels on bars
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2.0, height + 1, f'{height:.1f}%', ha

plt.tight_layout()
plt.show()
```

```
No data for US
```



Key Findings

This analysis compares the percentage of the population vaccinated against COVID-19 in five countries: Kenya, India, United Kingdom, South Africa, and Australia. The data reveals significant disparities in vaccination coverage across these nations.

Key Insights:

1. **Australia Leads Vaccination Efforts:** Australia exhibits the highest vaccination rate at 82.7%, indicating a strong rollout and high adoption of vaccines within the country.
2. **Kenya Lags Significantly:** Kenya demonstrates the lowest vaccination rate, with only 20.5% of its population vaccinated. This stark contrast highlights a potential struggle in vaccine access, distribution, or acceptance compared to other nations in the analysis.
3. **India Shows Strong Progress:** Despite its large population, India has achieved a high vaccination rate of 75.2%, suggesting a successful large-scale vaccination campaign.
4. **United Kingdom and South Africa Show Mid-Range Performance:** The United Kingdom (67.2%) and South Africa (35.1%) fall between the leaders and laggards, indicating moderate success with room for improvement in their vaccination programs.
5. **Developed vs. Developing Nations:** A potential correlation emerges between economic development and vaccination rates, with developed nations (Australia, UK) generally outperforming developing nations (Kenya, South Africa).
6. **Regional Differences within Developing Economies:** The contrast between India's and South Africa's vaccination rates highlights the importance of considering regional factors and policy choices within similar economic contexts.
7. **Need for Global Equity:** The significant gap between the highest and lowest vaccination rates underscores the ethical and practical necessity of ensuring fair and equitable global vaccine distribution.

Anomalies and Interesting Patterns:

- The wide range in vaccination rates (from 20.5% to 82.7%) is the most prominent pattern. This suggests that factors such as economic development, healthcare infrastructure, public health policies, and public trust in vaccines could be playing a significant role in the varying success of vaccination campaigns.
- It's interesting to note the difference between India and South Africa, both developing economies. India has achieved a much higher vaccination rate, which could be attributed to different policy priorities, resource allocation, or population density influencing distribution strategies.

In [34]:

```
pip install plotly
```

```
Requirement already satisfied: plotly in c:\users\priscillah\anaconda3\envs\learn-env\lib\site-packages (6.0.1)
Requirement already satisfied: narwhals>=1.15.1 in c:\users\priscillah\anaconda3\envs\learn-env\lib\site-packages (from plotly) (1.38.0)
Requirement already satisfied: packaging in c:\users\priscillah\appdata\roaming\python\python313\site-packages (from plotly) (24.2)
```

```
Note: you may need to restart the kernel to use updated packages.
```

In [35]:

```python
import plotly.express as px
```

In [36]:

```python
# Get the latest data
latest_data = df1.groupby('country').last().reset_index()
latest_data = latest_data[['iso_code', 'cases_total']]
```

In [37]:

```python
fig = px.choropleth(latest_data,
                    locations='iso_code',  # Column with country codes
                    color='cases_total',  # Column with the data to visualize
                    hover_name='iso_code',  # Column to show on hover
                    title='Total COVID-19 Cases by Country (Latest Data)',
                    color_continuous_scale=px.colors.sequential.Plasma)  # Ch
fig.show()
```

In [ ]: