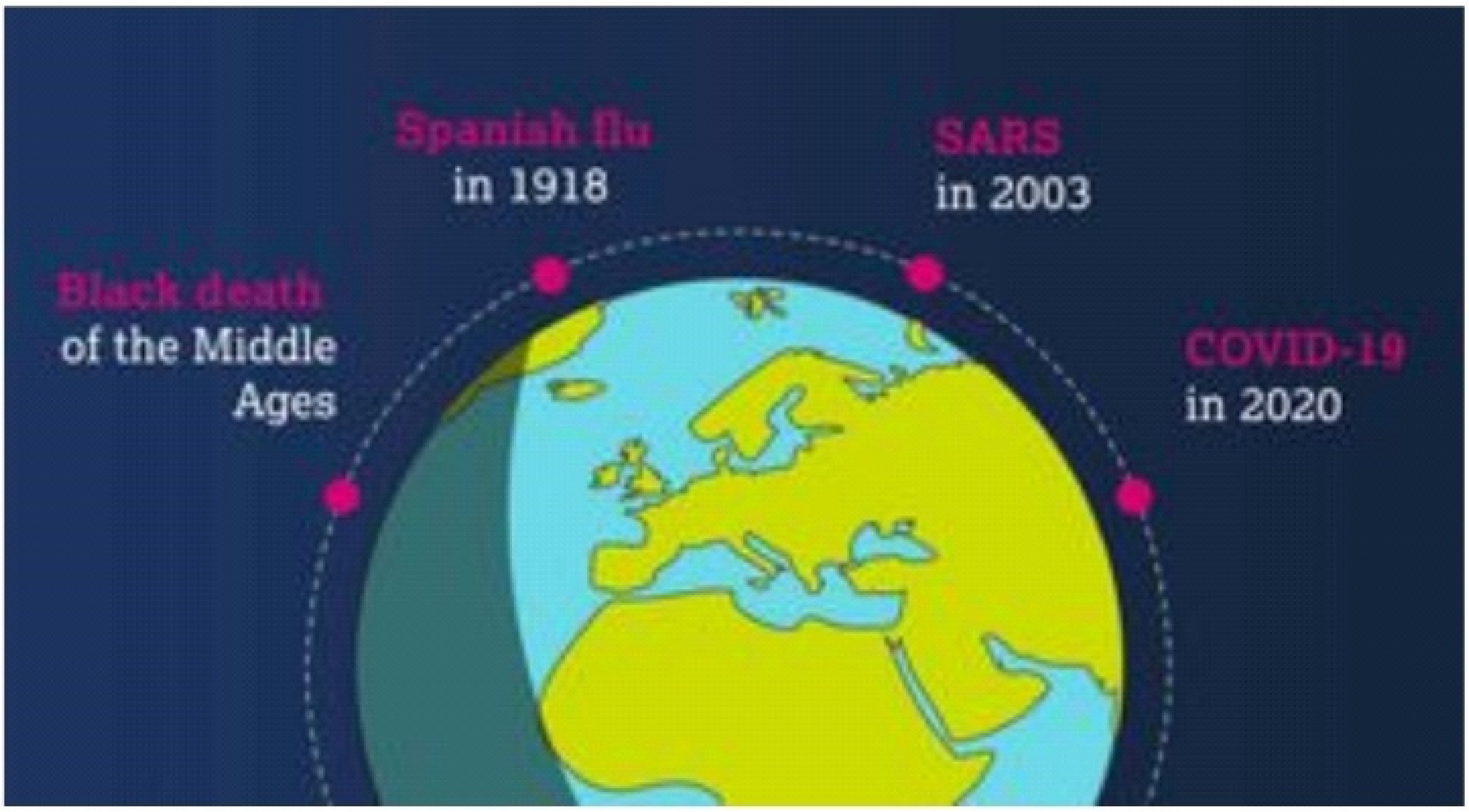
COVID 19 VACCINES ANALYSIS



Infectious disease pandemics such as influenza (flu) and COVID-19 continue to have a major social and economic impact on affected populations.

Abstract

Objective The COVID-19 vaccination program in India started after the first wave of infections had almost subsided. In this work, the objective is to perform a statewise analysis to assess the impact of vaccination during the second COVID-19 wave in India. A total of 21 states are chosen for the analysis encompassing 97% of the Indian population.

Methods We use the generalized Gompertz curve to study the COVID-19 outbreak. The generalized Gompertz model is then modified to study the impact of vaccination. The modified model considers the cumulative daily number of individuals having the first and second shots of the vaccine in each state as explanatory variables.

Table of contents

Aim:-
This project aims to analyze data in detail on vaccinated people and fully vaccinated by year and country.

Introduction:-
The main objective of this project is to analyze the data on, COVID-19 Vaccinations. Through the Analysis of data, we can find out some important insights.

Problem Statement:-

• We can find out how many people are completely vaccinated.
• Total vaccinations by each year and then by country. In this analysis, we can see the number of people vaccinated per hundred.

Methodology:-
Step 1: Data cleaning
In data cleaning I cleaned the data with the transform data option present in Power BI because the dataset was not cleaned and included some missing values, so with the help of the duplicates function in Power BI, I cleaned the data and replace the null values with 0 and then started working on it.


How to protect ourselves & others
9 important COVID-19 prevention measures
01 Stay home and self-isolate if you feel unwell, even with mild symptoms
02 Clean hands frequently with soap & water for 40 seconds or with alcohol-based hand rub
03 Cover your nose and mouth with a disposable tissue or flexed elbow when you cough or sneeze
04 Avoid touching your eyes, nose and mouth
05 Maintain a minimum physical distance of at least 1 metre from others
06 Stay away from crowds and avoid poorly ventilated indoor spaces
07 Use a fabric mask where physical distancing of at least 1 metre is not possible
08 Use a medical / surgical mask if you may be at higher risk (age, medical conditions)
09 Regularly clean & disinfect frequently touched surfaces

Step 2: Data interpretation

In this data interpretation step, I found out some important information about the data set.

- The data set was almost clear and completed.
- I replaced the null values with 0.
- There is total of 86512 rows and 15 columns.

Step 3: Visualization

In visualization, I took the help of Power BI Desktop software to make graphs and charts here some relevant graphs and charts are attached.

Analysis (Data sheets pertaining to it):-

In observation found some interesting points that are mentioned below.

• According to data on people fully vaccinated in the year.

• The dataset available is from 2020 to 2021

• Total vaccination by the country in map visualization.

• Total Highest Daily vaccination is 9223133948 in 2021.

• Total Highest vaccination is 704952663700 in China.

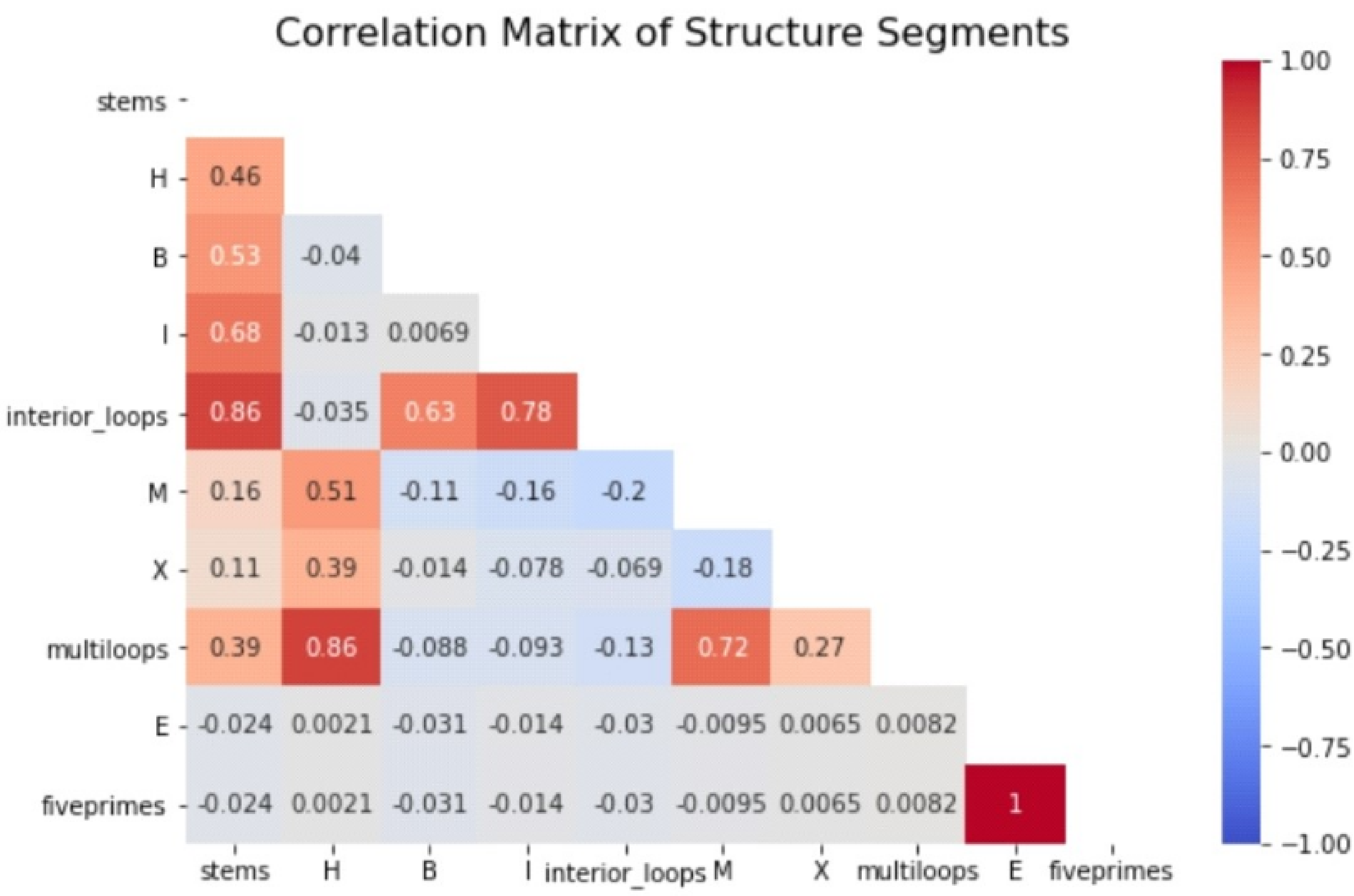
• Highest number of vaccinations by the source name is the Ministry of Health is 7.41K.

• Top 10 countries with fully vaccinated:

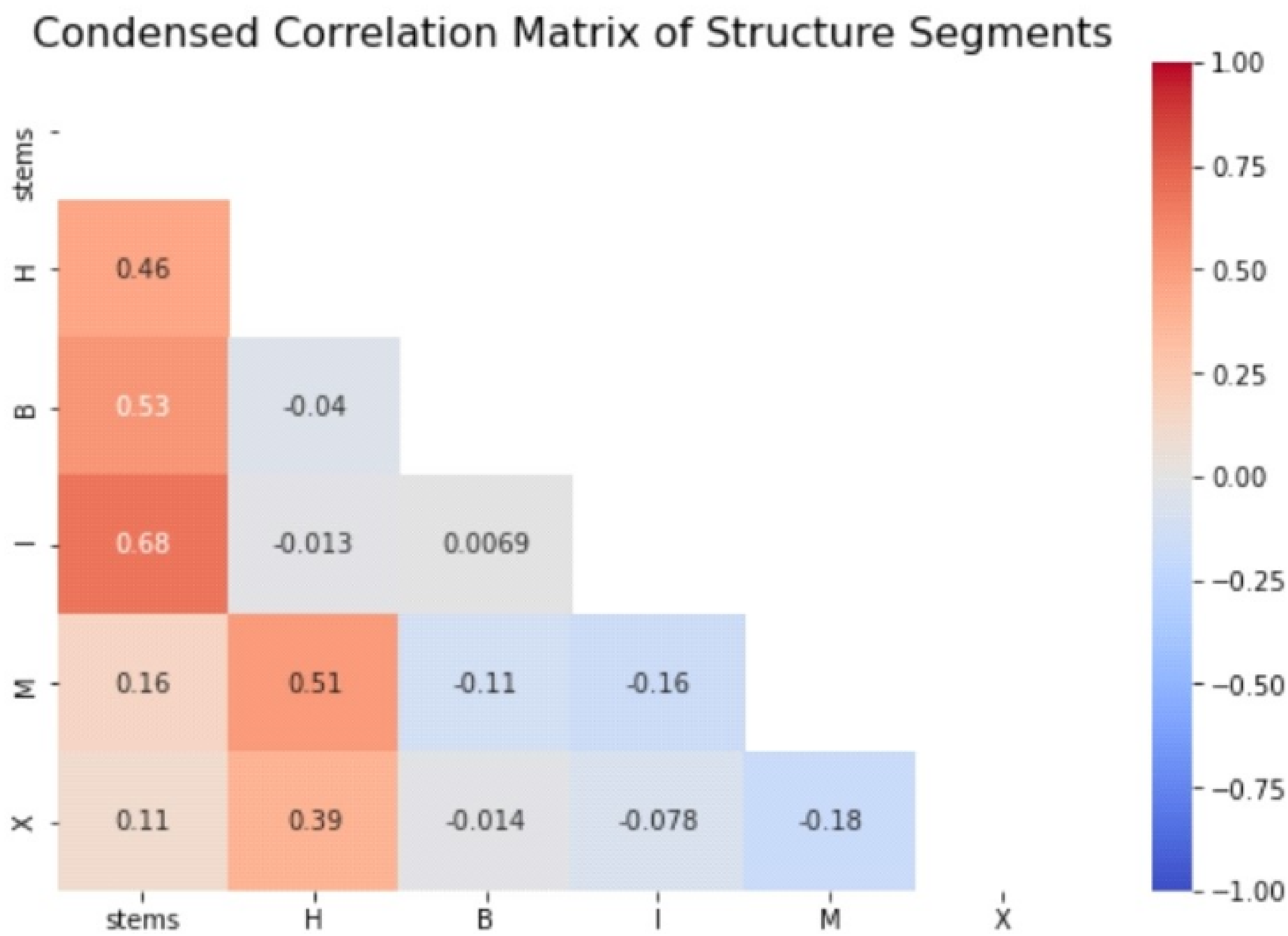
• Top 10 Daily vaccination in the countries:

Top 10 countries with the top 10 vaccine

Top 10 Countries where most people



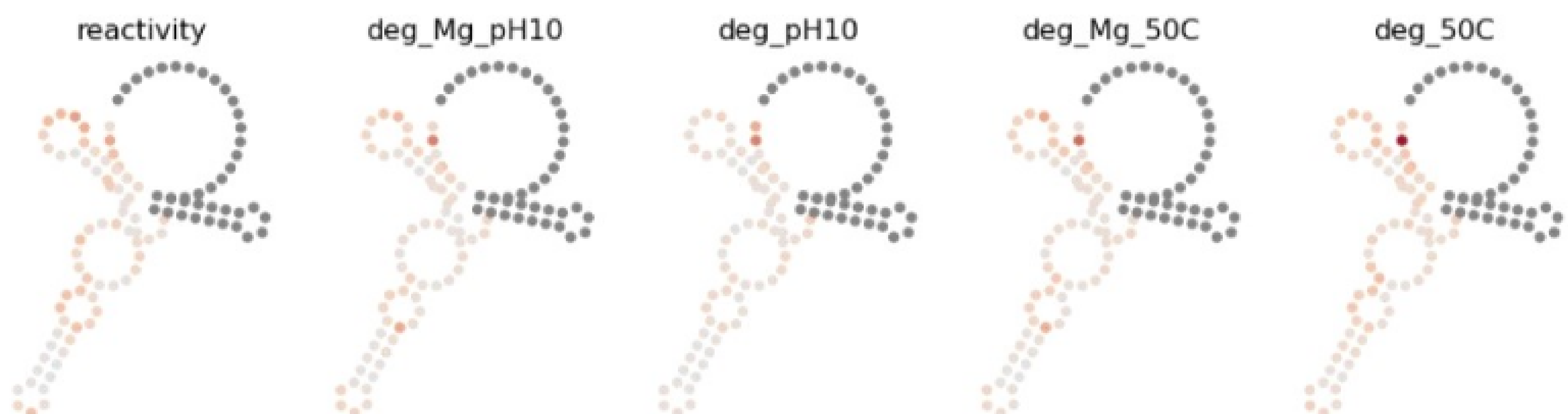
Correlation Matrix of Structure Segments
stems
H
B
I
interior_loops
M
X
multiloops
E
fiveprimes
0.46
0.53
-0.04
0.68
-0.013
0.0069
0.86
-0.035
0.63
0.78
0.16
0.51
-0.11
-0.16
-0.2
0.11
0.39
-0.014
-0.078
-0.069
-0.18
0.39
0.86
-0.088
-0.093
-0.13
0.72
0.27
-0.024
0.0021
-0.031
-0.014
-0.03
-0.0095
0.0065
0.0082
-0.024
0.0021
-0.031
-0.014
-0.03
-0.0095
0.0065
0.0082
1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

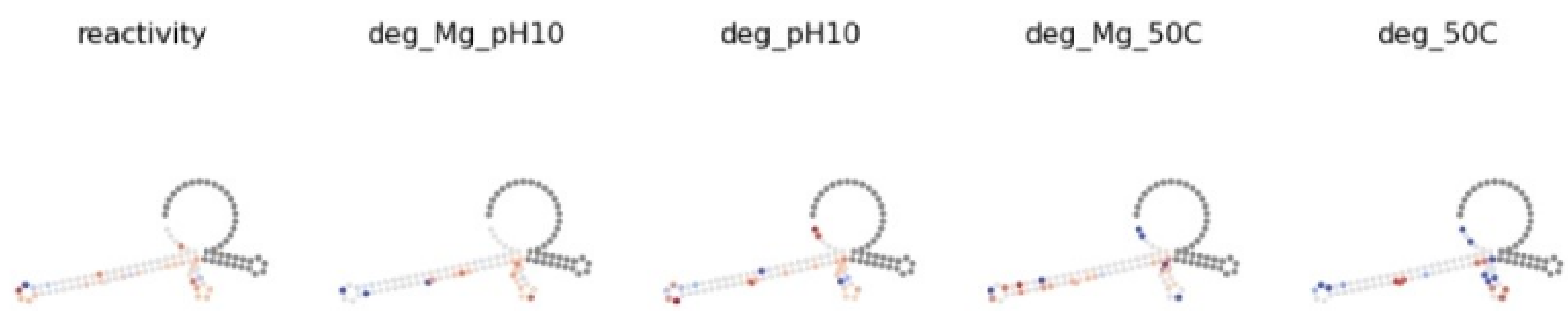


Insights:-

- In conclusion, we can take a look at the final Report for further analysis.
- We can see the top 10 sources.
- Countries by fully vaccination etc.

OpenVaccine: EDA & Feature Engineering with Forgi





Current global situation

- 75 million cases
- 5 countries with highest cumulative number of cases
    1. United States of America
    2. India
    3. Brazil
    4. Russian Federation
    5. France

- 1,68 million deaths
- 5 countries with highest cumulative number of death

    1.United States of America

    2.Brazil

    3.India

    4.Mexico

    5.Italy

Global level

Availability: One of the most critical challenges for LMICs currently is to get sufficient supplies of vaccine and to sustain the level of supplies needed. In September last year, Oxfam reported that the richer nations -with just 13% of the world's population - secured more than half of the supplies of the five leading vaccine candidates at that time. The COVID-19 Vaccine Global Access Facility (COVAX) has been established to ensure rapid, fair and equitable distribution of the vaccine across the globe. The success of COVAX will be a key determinant for ensuring availability of vaccines in LMICs with 67 low income countries relying on COVAX for their vaccine supplies.

Affordability: The price of vaccines will certainly be a major factor in countries' ability to roll out mass vaccination. Prices of the approved vaccines vary widely, reported as ranging from USD 6 to USD 74 per dose. COVAX alone will not be able to meet the demand of LMICs for COVID-19 vaccines and countries' ability and affordability to secure additional vaccine, possibility at a higher cost, will be critical for vaccine roll-out, especially at the early stage.

National level

Political commitment: Strong political commitment is crucial for the success of a massive initiative such as the roll-out of Covid-19 vaccines. A recent panel discussion of members of parliaments from several countries, including LMICs, led by Lord Boateng of the UK Parliament identified cross -party, financial, legal, civil-society and grassroots commitments as the cornerstones for success of national immunization. These domestic political commitments are equally, if not more,

Individual level

Vaccine hesitancy: Covid-19 vaccination hesitancy is strong and widespread in many parts of the world. Thankfully, prior evidences suggests that in LMICs vaccine coverage is mainly correlated with supply side factors such as vaccine availability, whereas in high income countries it is more correlated with personal belief. However, increasing rumours linked to social and digital media are leading to growing mistrust of vaccines and vaccine trials in LMICs. Effective and targeted community engagement and communication campaigns can help in mitigating vaccine hesitancy in countries where the risk is substantial.

Documentation:

1. Introduction:

- Briefly introduce the project, its goals, and the context of COVID-19.

2. Data Collection:

- Describe the data sources you used, including their reliability and update frequency.

3. Data Preprocessing:

- Explain how you cleaned and prepared the data for analysis.

4. Analysis Methods:

- Detail the statistical and analytical methods you used, including any models or algorithms.

5. Results and Insights:

- Present your findings with clear visualizations and explanations.

6. Discussion:

- Interpret the results and discuss their implications. Consider the limitations of your analysis.

python code integration

[redacted]

```
In [2]: import pandas as pd
```

```
In [16]: import pandas as pd
         df = pd.read_csv(r"C:\Users\Machines\Downloads\country_vaccinations.csv\country_vaccinations.csv")
         print(df)
```

```
           country iso_code        date  total_vaccinations  \
0      Afghanistan      AFG  2021-02-22                 0.0
1      Afghanistan      AFG  2021-02-23                 NaN
2      Afghanistan      AFG  2021-02-24                 NaN
3      Afghanistan      AFG  2021-02-25                 NaN
4      Afghanistan      AFG  2021-02-26                 NaN
...            ...      ...         ...                 ...
86507     Zimbabwe      ZWE  2022-03-25           8691642.0
86508     Zimbabwe      ZWE  2022-03-26           8791728.0
86509     Zimbabwe      ZWE  2022-03-27           8845039.0
86510     Zimbabwe      ZWE  2022-03-28           8934360.0
86511     Zimbabwe      ZWE  2022-03-29           9039729.0

       people_vaccinated  people_fully_vaccinated  daily_vaccinations_raw  \
0                    0.0                      NaN                     NaN
1                    NaN                      NaN                     NaN
2                    NaN                      NaN                     NaN
3                    NaN                      NaN                     NaN
4                    NaN                      NaN                     NaN
...                  ...                      ...                     ...
86507          4814582.0                3473523.0                139213.0
86508          4886242.0                3487962.0                100086.0
86509          4918147.0                3493763.0                 53311.0
86510          4975433.0                3501493.0                 89321.0
86511          5053114.0                3510256.0                105369.0

       daily_vaccinations  total_vaccinations_per_hundred  \
0                     NaN                            0.00
1                  1367.0                             NaN
2                  1367.0                             NaN
3                  1367.0                             NaN
4                  1367.0                             NaN
...                   ...                             ...
86507             69579.0                           57.59
86508             83429.0                           58.25
86509             90629.0                           58.61
86510            100614.0                           59.20
86511            103751.0                           59.90

       people_vaccinated_per_hundred  people_fully_vaccinated_per_hundred  \
0                               0.00                                  NaN
1                                NaN                                  NaN
```

[redacted]

[redacted]

```
86507     Zimbabwe      ZWE  2022-03-25          8691642.0
86508     Zimbabwe      ZWE  2022-03-26          8791728.0
86509     Zimbabwe      ZWE  2022-03-27          8845039.0
86510     Zimbabwe      ZWE  2022-03-28          8934360.0
86511     Zimbabwe      ZWE  2022-03-29          9039729.0

       people_vaccinated  people_fully_vaccinated  daily_vaccinations_raw  \
0                    0.0                      0.0                     0.0
1                    0.0                      0.0                     0.0
2                    0.0                      0.0                     0.0
3                    0.0                      0.0                     0.0
4                    0.0                      0.0                     0.0
...                  ...                      ...                     ...
86507          4814582.0                3473523.0                139213.0
86508          4886242.0                3487962.0                100086.0
86509          4918147.0                3493763.0                 53311.0
86510          4975433.0                3501493.0                 89321.0
86511          5053114.0                3510256.0                105369.0

       daily_vaccinations  total_vaccinations_per_hundred  \
0                     0.0                            0.00
1                  1367.0                            0.00
2                  1367.0                            0.00
3                  1367.0                            0.00
4                  1367.0                            0.00
...                   ...                             ...
86507             69579.0                           57.59
86508             83429.0                           58.25
86509             90629.0                           58.61
86510            100614.0                           59.20
86511            103751.0                           59.90

       people_vaccinated_per_hundred  people_fully_vaccinated_per_hundred  \
0                               0.00                                 0.00
1                               0.00                                 0.00
2                               0.00                                 0.00
3                               0.00                                 0.00
4                               0.00                                 0.00
...                              ...                                  ...
86507                          31.90                                23.02
86508                          32.38                                23.11
86509                          32.59                                23.15
86510                          32.97                                23.20
86511                          33.48                                23.26

       daily_vaccinations_per_million  \
0                                 0.0
1                                34.0
2                                34.0
3                                34.0
```

[redacted]

[redacted]

```
0                          https://covid19.who.int/
1                          https://covid19.who.int/
2                          https://covid19.who.int/
3                          https://covid19.who.int/
4                          https://covid19.who.int/
...                                             ...
86507  https://www.arcgis.com/home/webmap/viewer.html...
86508  https://www.arcgis.com/home/webmap/viewer.html...
86509  https://www.arcgis.com/home/webmap/viewer.html...
86510  https://www.arcgis.com/home/webmap/viewer.html...
86511  https://www.arcgis.com/home/webmap/viewer.html...

[86512 rows x 15 columns]
```

In [17]:
```
df.head()
```

Out[17]:

	country	iso_code	date	total_vaccinations	people_vaccinated	people_fully_vaccinated	daily_vaccinations_raw	daily_vaccinations	total_vaccinations_per_
0	Afghanistan	AFG	2021-02-22	0.0	0.0	NaN	NaN	NaN	
1	Afghanistan	AFG	2021-02-23	NaN	NaN	NaN	NaN	1367.0	
2	Afghanistan	AFG	2021-02-24	NaN	NaN	NaN	NaN	1367.0	
3	Afghanistan	AFG	2021-02-25	NaN	NaN	NaN	NaN	1367.0	
4	Afghanistan	AFG	2021-02-26	NaN	NaN	NaN	NaN	1367.0	

In [23]:
```
#filling missing values
df.fillna(0, inplace=True)
print(df.head())
```

```
       country iso_code        date  total_vaccinations  people_vaccinated  \
0  Afghanistan      AFG  2021-02-22                 0.0                0.0
1  Afghanistan      AFG  2021-02-23                 0.0                0.0
2  Afghanistan      AFG  2021-02-24                 0.0                0.0
3  Afghanistan      AFG  2021-02-25                 0.0                0.0
4  Afghanistan      AFG  2021-02-26                 0.0                0.0

   people_fully_vaccinated  daily_vaccinations_raw  daily_vaccinations  \
0                      0.0                     0.0                 0.0
```

[redacted]

[redacted]

```
   people_fully_vaccinated  daily_vaccinations_raw  daily_vaccinations  \
0                      0.0                     0.0                 0.0
1                      0.0                     0.0              1367.0
2                      0.0                     0.0              1367.0
3                      0.0                     0.0              1367.0
4                      0.0                     0.0              1367.0

   total_vaccinations_per_hundred  people_vaccinated_per_hundred  \
0                             0.0                            0.0
1                             0.0                            0.0
2                             0.0                            0.0
3                             0.0                            0.0
4                             0.0                            0.0

   people_fully_vaccinated_per_hundred  daily_vaccinations_per_million  \
0                                  0.0                             0.0
1                                  0.0                            34.0
2                                  0.0                            34.0
3                                  0.0                            34.0
4                                  0.0                            34.0

                                       vaccines  \
0  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
1  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
2  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
3  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
4  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...

                source_name            source_website
0  World Health Organization  https://covid19.who.int/
1  World Health Organization  https://covid19.who.int/
2  World Health Organization  https://covid19.who.int/
3  World Health Organization  https://covid19.who.int/
4  World Health Organization  https://covid19.who.int/
```

In [24]:

```
#Processing Data
#eliminating missing value
print(df.dropna())
```

```
           country iso_code        date  total_vaccinations  \
0      Afghanistan      AFG  2021-02-22                 0.0
1      Afghanistan      AFG  2021-02-23                 0.0
2      Afghanistan      AFG  2021-02-24                 0.0
3      Afghanistan      AFG  2021-02-25                 0.0
4      Afghanistan      AFG  2021-02-26                 0.0
...            ...      ...         ...                 ...
86507     Zimbabwe      ZWE  2022-03-25           8691642.0
86508     Zimbabwe      ZWE  2022-03-26           8791728.0
86509     Zimbabwe      ZWE  2022-03-27           8845039.0
```

[redacted]

[redacted]

```
1                           34.0
2                           34.0
3                           34.0
4                           34.0
...                          ...
86507                     4610.0
86508                     5528.0
86509                     6005.0
86510                     6667.0
86511                     6874.0

                                              vaccines  \
0      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
1      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
2      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
3      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
4      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
...                                                 ...
86507  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86508  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86509  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86510  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86511  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...

                    source_name  \
0      World Health Organization
1      World Health Organization
2      World Health Organization
3      World Health Organization
4      World Health Organization
...                          ...
86507         Ministry of Health
86508         Ministry of Health
86509         Ministry of Health
86510         Ministry of Health
86511         Ministry of Health

                                         source_website
0                                https://covid19.who.int/
1                                https://covid19.who.int/
2                                https://covid19.who.int/
3                                https://covid19.who.int/
4                                https://covid19.who.int/
...                                                 ...
86507  https://www.arcgis.com/home/webmap/viewer.html...
86508  https://www.arcgis.com/home/webmap/viewer.html...
86509  https://www.arcgis.com/home/webmap/viewer.html...
86510  https://www.arcgis.com/home/webmap/viewer.html...
86511  https://www.arcgis.com/home/webmap/viewer.html...
```

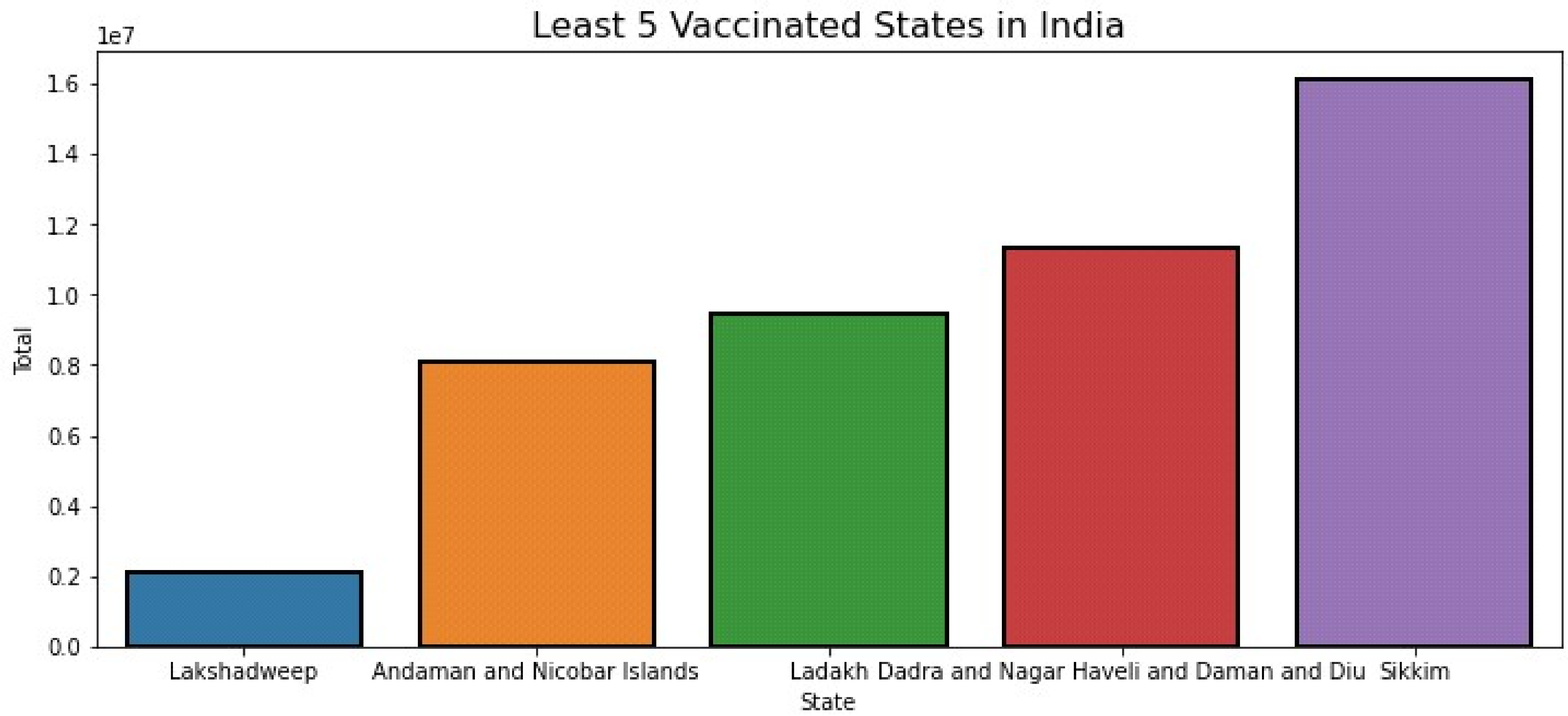
[redacted]

```
       people_vaccinated_per_hundred  people_fully_vaccinated_per_hundred  \
0                               0.00                                  NaN
1                                NaN                                  NaN
2                                NaN                                  NaN
3                                NaN                                  NaN
4                                NaN                                  NaN
...                              ...                                  ...
86507                          31.90                                23.02
86508                          32.38                                23.11
86509                          32.59                                23.15
86510                          32.97                                23.20
86511                          33.48                                23.26

       daily_vaccinations_per_million  \
0                                 NaN
1                                34.0
2                                34.0
3                                34.0
4                                34.0
...                               ...
86507                          4610.0
86508                          5528.0
86509                          6005.0
86510                          6667.0
86511                          6874.0

                                                vaccines  \
0      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
1      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
2      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
3      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
4      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi...
...                                                  ...
86507  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86508  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86509  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86510  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...
86511  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac...

                     source_name  \
0      World Health Organization
1      World Health Organization
2      World Health Organization
3      World Health Organization
4      World Health Organization
...                          ...
86507         Ministry of Health
86508         Ministry of Health
86509         Ministry of Health
86510         Ministry of Health
```




```
df.people_vaccinated = df.people_vaccinated.astype(int)

df.people_fully_vaccinated = df.people_fully_vaccinated.astype(int)

df.daily_vaccinations_raw = df.daily_vaccinations_raw.astype(int)

df.daily_vaccinations = df.daily_vaccinations.astype(int)

df.total_vaccinations_per_hundred = df.total_vaccinations_per_hundred.astype(int)

df.people_fully_vaccinated_per_hundred =
df.people_fully_vaccinated_per_hundred.astype(int)

df.daily_vaccinations_per_million = df.daily_vaccinations_per_million.astype(int)

df.people_vaccinated_per_hundred = df.people_vaccinated_per_hundred.astype(int)

date = df.date.str.split('-', expand =True)

date
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4568 entries, 0 to 4567
Data columns (total 15 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   country                              4568 non-null   object
 1   iso_code                             4260 non-null   object
 2   date                                 4568 non-null   object
 3   total_vaccinations                   2988 non-null   float64
 4   people_vaccinated                    2541 non-null   float64
 5   people_fully_vaccinated              1702 non-null   float64
 6   daily_vaccinations_raw               2523 non-null   float64
 7   daily_vaccinations                   4409 non-null   float64
 8   total_vaccinations_per_hundred       2988 non-null   float64
 9   people_vaccinated_per_hundred        2541 non-null   float64
 10  people_fully_vaccinated_per_hundred  1702 non-null   float64
 11  daily_vaccinations_per_million       4409 non-null   float64
 12  vaccines                             4568 non-null   object
 13  source_name                          4568 non-null   object
 14  source_website                       4568 non-null   object
dtypes: float64(9), object(6)
memory usage: 535.4+ KB
```

Incubation period of covid-19 from exposure start to symptoms onset [20]:

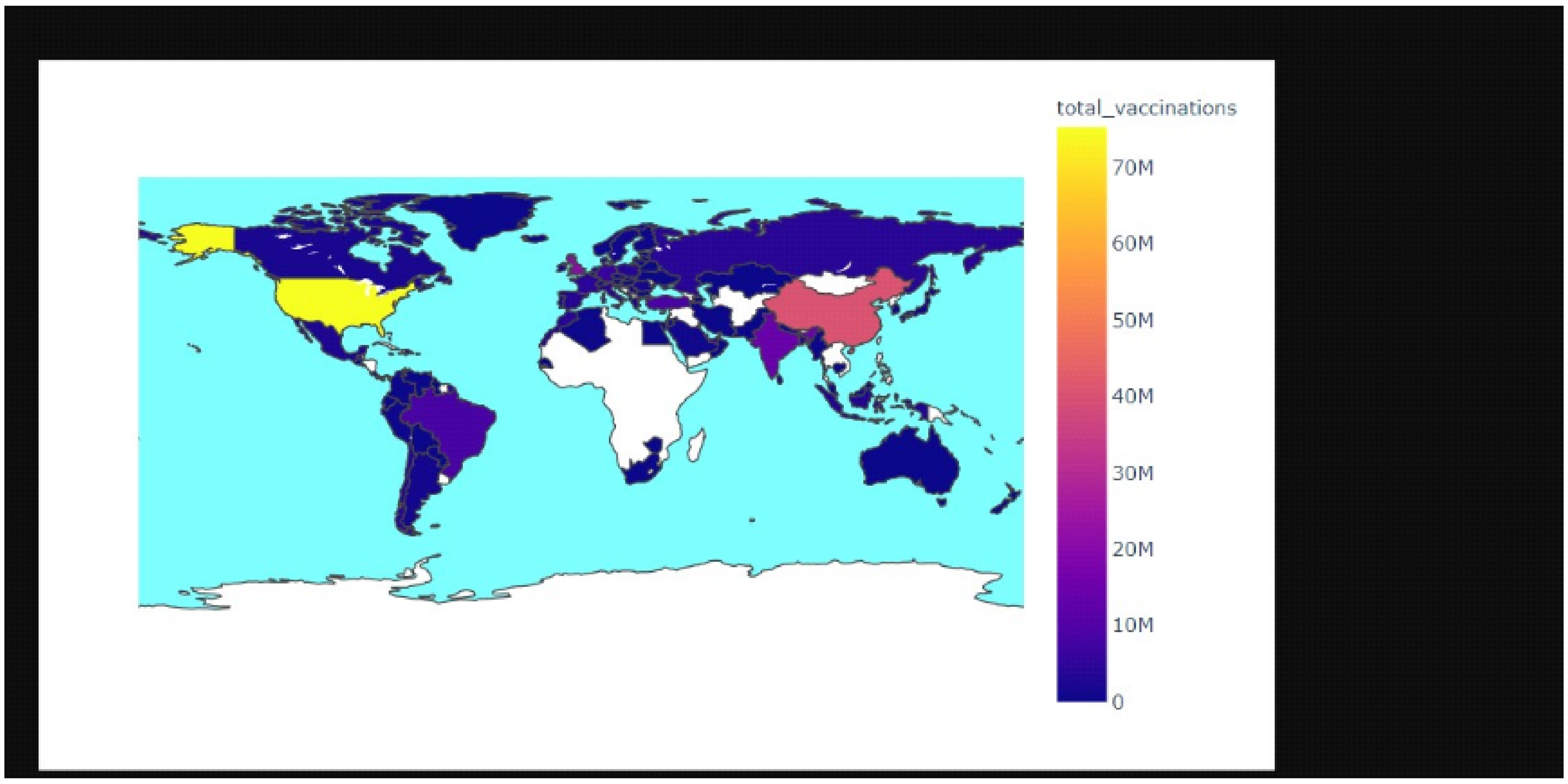
Days	Cases
1	4
2	5
3	3
4	11
5	11
6	9
7	5
8	8
9	7
10	4
11	2
12	2
13	2
14	0
Total	**73**

Incubation period of covid-19 from symptom onset to hospital visit [20]:

Days	Cases
1	221
2	48
3	41
4	30
5	27
6	17
7	20
8	17
9	2
10	3
11	2
12	18
13	1
14	5
Total	**452**

Infected people of different countries according to temperature domain [12,23,24]:

Country	Temperature domain	Temperature range (◦C)	Average yearly temperature (◦C)	Confirmed cases
Switzerland	Cold Temperate	(0-10)	5.50	24,551
China	Mix of Warm, Cold and Polar Temperate	(10-18) or (0-10)	6.95	81,953
UK	Cold Temperate	(0-10)	8.45	73,758
Germany	Cold Temperate	(0-10)	8.50	122,171
USA	Mostly Warm Temperate, and Cold Temperate	(10-18) or (0-10)	8.55	502,876
Belgium	Cold Temperate	(0-10)	9.55	26,667
Spain	Warm Temperate	(10-18)	13.30	158,273
Italy	Warm Temperate	(10-18)	13.45	147,577
Iran	Sub Tropical, and Warm temperate	(18-24) or (10-18)	17.25	68,192
South Africa	Mostly Warm Temperate	(10-18)	17.75 17.75	2003
India	Tropical Temperate	(24-34)	23.65	7,600
Saudi Arabia	Tropical, and Sub Tropical Temperate	(24-34) or (18-24)	24.65	3651
Oman	Tropical Temperate	(24-34)	25.60	484
Sudan	Tropical, and Sub Tropical Temperate	(24-34) or (18-24)	26.90	17



describe() function in pandas used to get the statistics of each feature present in our dataset. Some of the information we get include count, max, min, standard deviation, median, etc. df.describe()

Covid Vaccination Progress | describe dataset unique() function in pandas helps to get unique values present in the feature.

df.country.unique() Unique

country values def

size(m,n): fig = plt.gcf();

fig.set_size_inches(m,n);

Word Art of Countries

Word Cloud is a unique way to get information from our dataset. The words are shown in the form of art where the size proportional depends on how much the particular word repeated in the dataset. This is made by using the WordCloud library. Check the below code on how to draw word cloud wordCloud = WordCloud(background_color='white',

max_font_size = 50).generate(' '.join(df.country))

plt.figure(figsize=(15,7)) plt.axis('off')

plt.imshow(wordCloud) plt.show()

Covid Vaccination Progress | wordart countries

Total Vaccinated Till Date

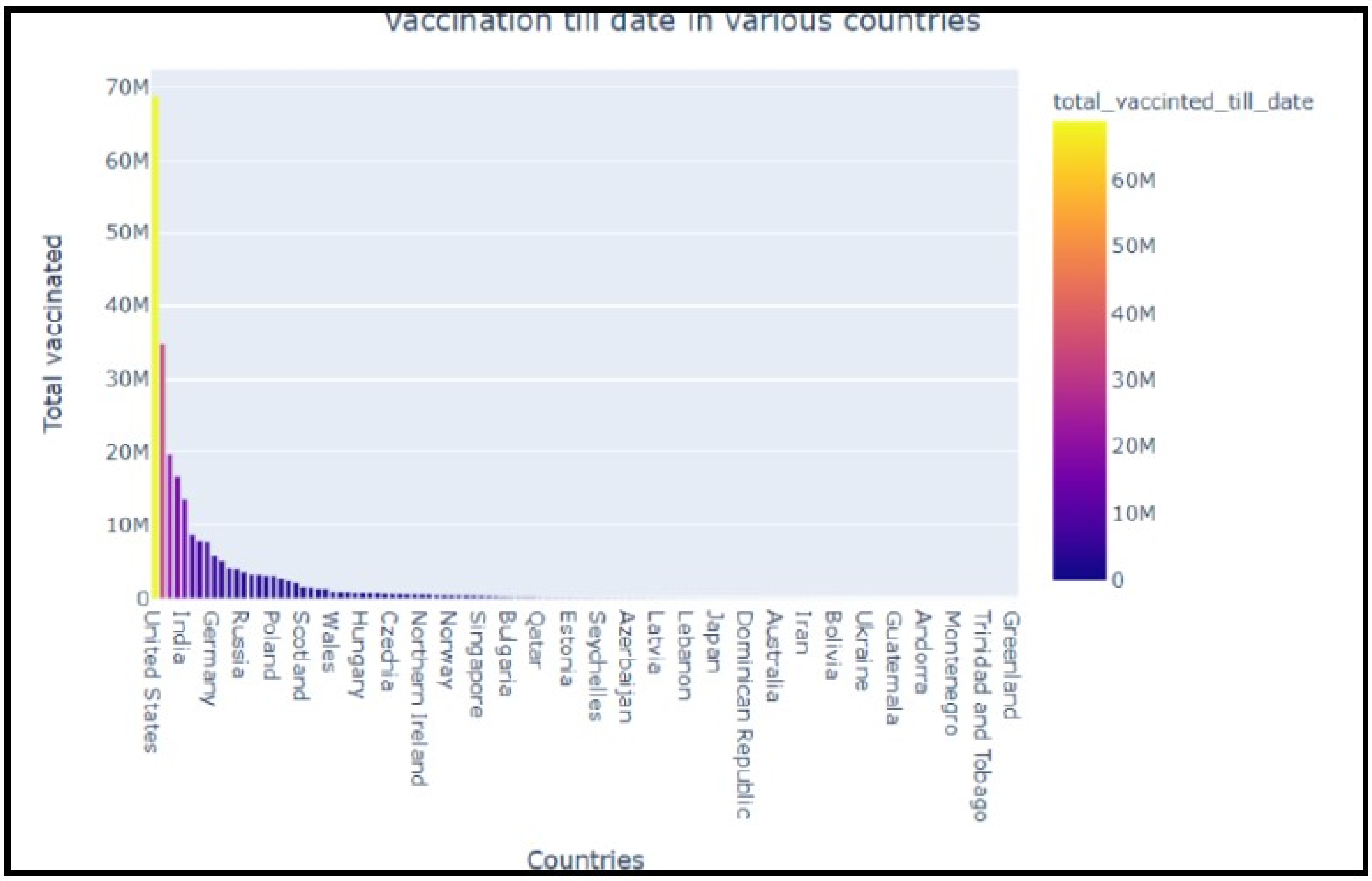
In this section, we are going to see how many total vaccines have been used in each country. Check the below code for more information. The data shows the United States has administrated most vaccines in the world followed by China, United Kingdom, England, India and at the last some countries includes Saint Helena, San Marino has 0 vaccination.

```
country_wise_total_vaccinated = {} for
country in df.country.unique() :
vaccinated = 0 for i in
range(len(df)) : if
df.country[i] == country :
vaccinated += df.daily_vaccinations[i] country_wise_total_vaccinated[country]
= vaccinated
# made a seperate dict from the df
country_wise_total_vaccinated_df =
pd.DataFrame.from_dict(country_wise_total_vaccinated,
orient='index', columns = ['total_vaccinted_till_date'])
# converted dict to df country_wise_total_vaccinated_df.sort_values(by =
'total_vaccinted_till_date', ascending = False, inplace = True)
country_wise_total_vaccinated_df
```

Total vaccinated

```
fig = px.bar(country_wise_total_vaccinated_df, y =
'total_vaccinted_till_date', x =
country_wise_total_vaccinated_df.index, color =
'total_vaccinted_till_date', color_discrete_sequence=
px.colors.sequential.Viridis_r
)
fig.update_layout(
title={
'text' : "Vaccination till date in various countries",
'y':0.95,
'x':0.5
```

```
},
xaxis_title="Countries", yaxis_title="Total
vaccinated", legend_title="Total
vaccinated"
)
fig.show()
```



Recommendations:-

- We can collect good datasets for analysis.
- We can analyze the data of the overall world.
- Like this dataset we can perform operations with various categories, city-wise or region-wise.

Conclusion:-

In conclusion, we can take a look at the final Report for further analysis. As we can see in the Report the top countries vaccination-wise, Top Country by the vaccination in daily and best top 10 countries with our vaccines. Vaccination peeks in 2022. The Top 2 vaccine sources are India, and China.