Importing Liberaries & Dataset

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.ticker import FuncFormatter

import warnings
warnings.filterwarnings("ignore")

url =
"https://raw.githubusercontent.com/modyreturn/Health_Care_Analysis/
refs/heads/master/merged_data.csv"

df = pd.read_csv(url)

df.head()
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Archive_Date","rawType":"object","type":"string"},
{"name":"Specialty_HIPE","rawType":"float64","type":"float"},
{"name":"Specialty_Name","rawType":"object","type":"string"},
{"name":"Adult_Child","rawType":"object","type":"string"},
{"name":"Age_Profile","rawType":"object","type":"string"},
{"name":"Time_Bands","rawType":"object","type":"string"},
{"name":"Total","rawType":"int64","type":"integer"},
{"name":"Case_Type","rawType":"object","type":"string"},
{"name":"Specialty
Group","rawType":"object","type":"string"}],"conversionMethod":"pd.Dat
aFrame","ref":"2091baf8-3828-4d8e-9a5b-97923d906dbf","rows":
[["0","2018-02-28","0.0","Small Volume Specialities","Adult","16-64","
0-3 Months","1","Day Case","Other"],["1","2018-02-28","0.0","Small
Volume Specialities","Adult","16-64"," 0-3 Months","1","Day
Case","Other"],["2","2018-02-28","0.0","Small Volume
Specialities","Adult","16-64"," 9-12
Months","1","Inpatient","Other"],["3","2018-02-28","0.0","Small Volume
Specialities","Adult","16-64"," 0-3 Months","1","Outpatient","Other"],
["4","2018-02-28","0.0","Small Volume Specialities","Adult","16-64","
0-3 Months","1","Outpatient","Other"]],"shape":{"columns":9,"rows":5}}

Cleaning The Data

```python
# converting Archive_Date to datetime
df['Archive_Date'] = pd.to_datetime(df['Archive_Date'])
df['Year'] = df['Archive_Date'].dt.year
df['Month_Name'] = df['Archive_Date'].dt.month_name()

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 452991 entries, 0 to 452990
Data columns (total 11 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   Archive_Date     452991 non-null  datetime64[ns]
 1   Specialty_HIPE   452800 non-null  float64
 2   Specialty_Name   452991 non-null  object
 3   Adult_Child      452991 non-null  object
 4   Age_Profile      452816 non-null  object
 5   Time_Bands       452989 non-null  object
 6   Total            452991 non-null  int64
 7   Case_Type        452991 non-null  object
 8   Specialty Group  452991 non-null  object
 9   Year             452991 non-null  int32
 10  Month_Name       452991 non-null  object
dtypes: datetime64[ns](1), float64(1), int32(1), int64(1), object(7)
memory usage: 36.3+ MB

df['Time_Bands'] = df['Time_Bands'].str.strip()
df['Age_Profile'] = df['Age_Profile'].str.strip()

# I will use the following func to format the values on axis of the
charts as needed
def millions_formatter(x, pos):
    if x >= 1_000_000:
        return f'{x*1.0/1_000_000:.1f}M'
    elif x >= 1_000:
        return f'{x*1.0/1_000:.1f}K'
    else:
        return f'{x:.0f}'

# Apply formatter to the current plot
formatter = FuncFormatter(millions_formatter)

# here you can categorise and order Month_Name to plot
month_order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug',
'Sep', 'Oct', 'Nov', 'Dec']
```

Exploratory Data Analysis (EDA):

Statistic Summary

```
# using describe() to get statistic summary for the data
df.describe(include=('all'))
```


```
{"columns":[{"name":"index","rawType":"object","type":"string"},
{"name":"Archive_Date","rawType":"object","type":"unknown"},
{"name":"Specialty_HIPE","rawType":"float64","type":"float"},
{"name":"Specialty_Name","rawType":"object","type":"unknown"},
```

{"name":"Adult_Child","rawType":"object","type":"unknown"},
{"name":"Age_Profile","rawType":"object","type":"unknown"},
{"name":"Time_Bands","rawType":"object","type":"unknown"},
{"name":"Total","rawType":"float64","type":"float"},
{"name":"Case_Type","rawType":"object","type":"unknown"},
{"name":"Specialty Group","rawType":"object","type":"unknown"},
{"name":"Year","rawType":"float64","type":"float"},
{"name":"Month_Name","rawType":"object","type":"unknown"}],"conversionMethod":"pd.DataFrame","ref":"ae655ce2-f096-4212-a8b2-7e07f9d77d66","rows":
[["count","452991","452800.0","452991","452991","452816","452989","452991.0","452991","452991","452991.0","452991"],
["unique",null,null,"78","3","3","8",null,"3","27",null,"12"],
["top",null,null,"General Surgery","Adult","16-64","0-3 Months",null,"Outpatient","General",null,"March"],
["freq",null,null,"43634","368151","203354","93818",null,"270281","76614",null,"47110"],["mean","2019-09-09 18:57:46.892720640","2619.1445759717312",null,null,null,null,"54.39005852213399",null,null,"2019.1817784459295",null],["min","2018-01-31 00:00:00","0.0",null,null,null,null,"1.0",null,null,"2018.0",null],
["25%","2018-10-31 00:00:00","1300.0",null,null,null,null,"3.0",null,null,"2018.0",null],
["50%","2019-08-31 00:00:00","1900.0",null,null,null,null,"13.0",null,null,"2019.0",null],["75%","2020-06-30 00:00:00","2600.0",null,null,null,null,"53.0",null,null,"2020.0",null],["max","2021-03-31 00:00:00","9000.0",null,null,null,null,"4239.0",null,null,"2021.0",null],
["std",null,"2362.043475185623",null,null,null,null,"120.7928371221548",null,null,"0.9635806573834385",null]],"shape":
{"columns":11,"rows":11}}

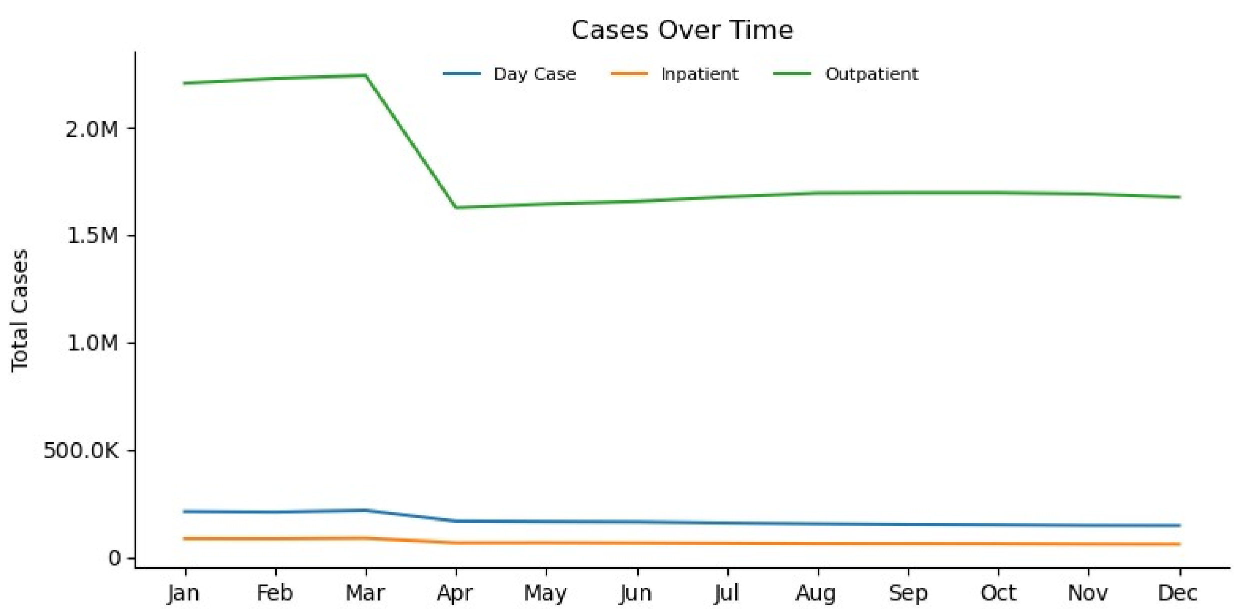
Cases Over Time:

- Now let's analyze Day Cases, Inpatient Cases, and Outpatient Cases over time.

```
cases_over_time = df.groupby(['Month_Name', 'Case_Type'])
['Total'].sum().reset_index()
cases_over_time['Month_Name'] = cases_over_time['Month_Name'].str[:3]
# to abbreviate the month name to the first 3 letters

cases_over_time.head()
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Month_Name","rawType":"object","type":"string"},
{"name":"Case_Type","rawType":"object","type":"string"},
{"name":"Total","rawType":"int64","type":"integer"}],"conversionMethod":"pd.DataFrame","ref":"baee13cb-584d-4664-8a07-e9627c7b9ae1","rows":
[["0","Apr","Day Case","168396"],["1","Apr","Inpatient","67712"],

```
["2","Apr","Outpatient","1626611"],["3","Aug","Day Case","156239"],
["4","Aug","Inpatient","64058"]],"shape":{"columns":3,"rows":5}}

# here you can categorise and order Month_Name to plot
month_order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug',
'Sep', 'Oct', 'Nov', 'Dec']
cases_over_time['Month_Name'] =
pd.Categorical(cases_over_time['Month_Name'], categories=month_order,
ordered=True)

plt.figure(figsize=(8, 4))

sns.lineplot(
    data=cases_over_time,
    x='Month_Name',
    y='Total',
    hue='Case_Type',
    palette='tab10'
)


plt.gca().yaxis.set_major_formatter(formatter)

plt.title('Cases Over Time')
plt.xlabel('')
plt.ylabel('Total Cases')
plt.legend(ncols=3, loc='upper center', framealpha=False, fontsize=8)

sns.despine()
plt.tight_layout()
plt.show()
```



Key Insights:

- Outpatient Cases
  - Outpatient volumes are **significantly higher** than other case types.
  - There is a **sharp decline between March and April**, followed by a stable trend.
- Day Case
  - Relatively stable across the year with a small dip in April, which mirrors the outpatient drop (but on a smaller scale).
  - This may suggest a system-wide effect in April (e.g., hospital capacity issues or a public holiday period)..
- Inpatient Cases
  - Lowest and **most stable** volume.
  - Very minimal month-to-month variation — this could indicate inpatient services are less affected by external factors or operate on a constant baseline.

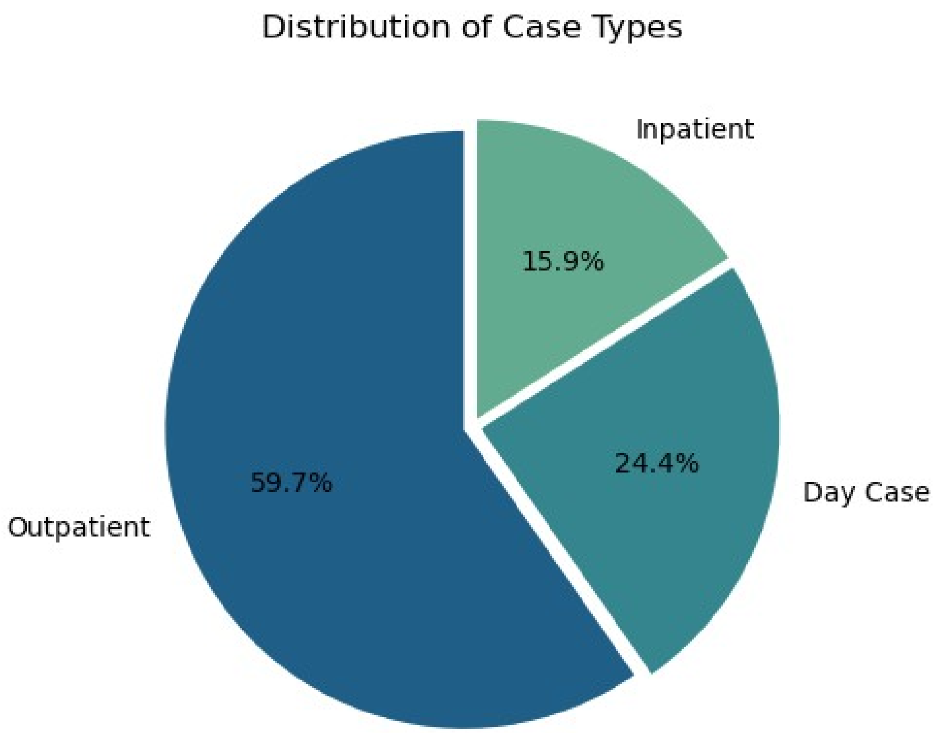
Cases Type Distributions:

- Let's see the distributions of Case Types

```
case_type_distribution = df['Case_Type'].value_counts().reset_index()
case_type_distribution.columns = ['Case_Type', 'Count']

case_type_distribution
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Case_Type","rawType":"object","type":"string"},
{"name":"Count","rawType":"int64","type":"integer"}],"conversionMethod
":"pd.DataFrame","ref":"d0e25764-85d8-4dee-9211-5c843761a63a","rows":
[["0","Outpatient","270281"],["1","Day Case","110487"],
["2","Inpatient","72223"]],"shape":{"columns":2,"rows":3}}

```
# Define the explode tuple dynamically
explode = [0.03] * len(case_type_distribution)

plt.figure(figsize=(10, 5))
plt.pie(
    case_type_distribution['Count'],
    labels=case_type_distribution['Case_Type'],
    colors=sns.color_palette('crest_r',
n_colors=len(case_type_distribution)),
    autopct='%1.1f%%',
    startangle=90,
    explode=explode
)

plt.title("Distribution of Case Types")
plt.show()
```



Key Insights

- Outpatient
  - Represents the **majority** of cases: **59.7%**.
  - Highlights the **dominance of non-admitted consultations** in the healthcare activity mix.
  - Indicates a likely emphasis on **preventive care, follow-ups, or minor procedures**.
- Day Case
  - Accounts for **24.4%** of total cases.
  - Suggests a **significant number of procedures are performed without overnight stays**.
  - Could be optimized further if infrastructure and patient conditions allow.
- Inpatient
  - Comprises only **15.9%** of the cases.
  - Indicates that **fewer cases require overnight hospitalization**, possibly due to efficiency or a lower acuity patient population.
  - Helps reduce overall healthcare costs and resource strain.

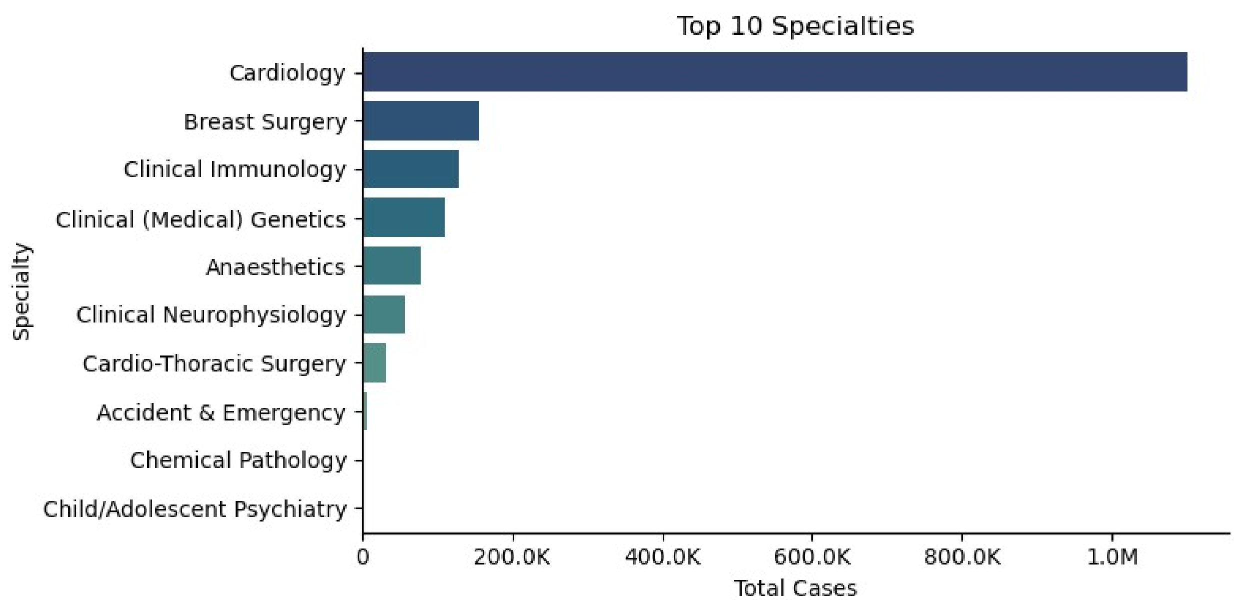
Specialty Analysis:

- Let's se what is the top 10 specialties in the dataset:

```python
#specialty_df = df.groupby(['Specialty_Name', 'Case_Type'])
['Total'].sum().reset_index()
specialty_df = df.groupby('Specialty_Name')
['Total'].sum().reset_index().head(10).sort_values(by='Total',
ascending=False)

specialty_df
```


{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Specialty_Name","rawType":"object","type":"string"},
{"name":"Total","rawType":"int64","type":"integer"}],"conversionMethod
":"pd.DataFrame","ref":"d65140da-b2b6-479f-804c-93ba55d75a02","rows":
[["4","Cardiology","1100604"],["2","Breast Surgery","156736"],
["8","Clinical Immunology","128125"],["7","Clinical (Medical)
Genetics","109024"],["1","Anaesthetics","78000"],["9","Clinical
Neurophysiology","56326"],["3","Cardio-Thoracic Surgery","31037"],
["0","Accident & Emergency","6004"],["5","Chemical Pathology","2891"],
["6","Child/Adolescent Psychiatry","2391"]],"shape":
{"columns":2,"rows":10}}


```python
plt.figure(figsize=(8, 4))
sns.barplot(
    data=specialty_df,
    y='Specialty_Name',
    x='Total',
    palette='crest_r'
)

# function to format the values on the yaxis
def millions_formatter(x, pos):
    if x >= 1_000_000:
        return f'{x*1.0/1_000_000:.1f}M'
    elif x >= 1_000:
        return f'{x*1.0/1_000:.1f}K'
    else:
        return f'{x:.0f}'

# Apply formatter to the current plot
formatter = FuncFormatter(millions_formatter)
plt.gca().xaxis.set_major_formatter(formatter)

plt.title('Top 10 Specialties')
plt.xlabel('Total Cases')
plt.ylabel('Specialty')

sns.despine()
plt.tight_layout()
plt.show()
```



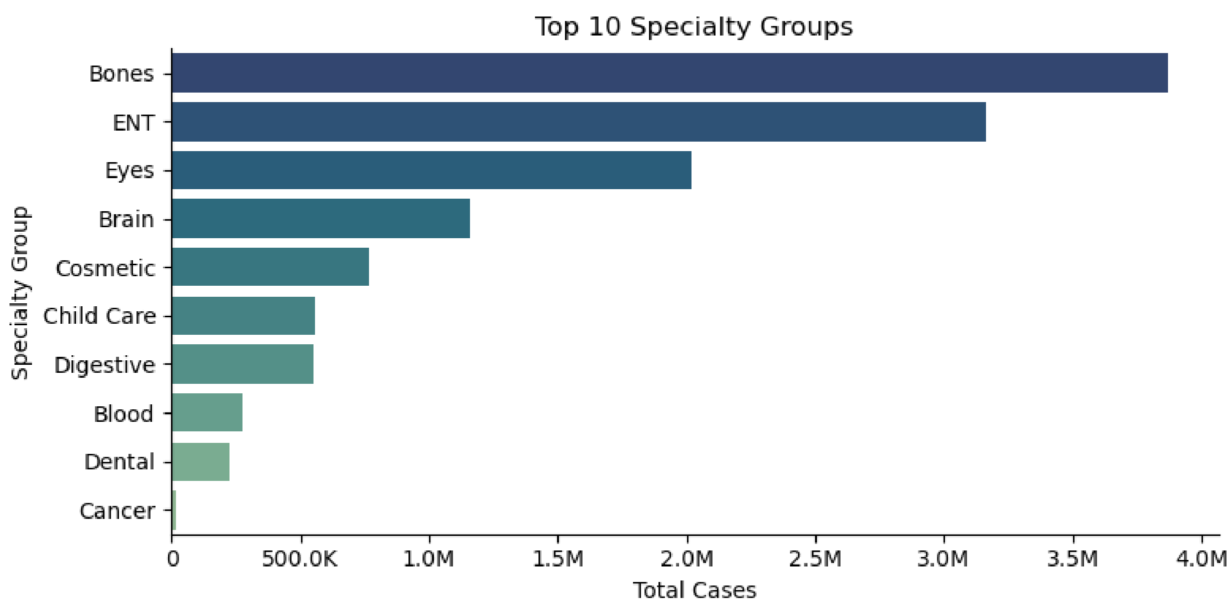
Key Insights

- Cardiology:
  - Dominates the chart with **over 1 million cases**.
  - Indicates high demand for heart-related services.
  - Suggests the need for continued investment in **cardiac care infrastructure and staff**.
- Breast Surgery & Clinical Immunology:
  - Each has over **100K cases**.
  - Reflects strong demand in **oncology and immune-related conditions**.
- Clinical (Medical) Genetics:
  - High volume indicates rising interest in **genomic medicine**.
- Anaesthetics & Clinical Neurophysiology:
  - Essential support specialties with **significant case volumes**.
  - Central to surgical and neurological diagnostic care.
- Cardio-Thoracic Surgery
  - Lower in volume than Cardiology, likely due to its **specialized nature**.
- Accident & Emergency
  - Lower than expected—possibly due to data scope or triage protocols.
- Chemical Pathology & Child/Adolescent Psychiatry
  - Critical for diagnostics and mental health support.
  - Smaller totals, but still among the top 10.

```
specialty_group = df.groupby('Specialty Group')
['Total'].sum().reset_index().head(10).sort_values(by='Total',
ascending=False)
specialty_group.head(5)
```

```
{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Specialty Group","rawType":"object","type":"string"},
{"name":"Total","rawType":"int64","type":"integer"}],"conversionMethod
":"pd.DataFrame","ref":"59684829-df3c-46a6-a8cf-2db353c78796","rows":
[["1","Bones","3872040"],["8","ENT","3164343"],["9","Eyes","2018252"],
["2","Brain","1159445"],["5","Cosmetic","769540"]],"shape":
{"columns":2,"rows":5}}
```


```
plt.figure(figsize=(8, 4))
sns.barplot(
    data=specialty_group,
    y='Specialty Group',
    x='Total',
    palette='crest_r'
)

# formatting the xaxis values
plt.gca().xaxis.set_major_formatter(formatter)

plt.title('Top 10 Specialty Groups')
plt.xlabel('Total Cases')
plt.ylabel('Specialty Group')

sns.despine()
plt.tight_layout()
plt.show()
```



Key Insights

1. Bones
    - **Highest total cases**, approaching **4 million**.

    - Indicates high demand for **orthopedic services**, likely due to aging populations or injury recovery needs.
2. ENT (Ear, Nose, Throat)
    - Second highest, with **over 3 million cases**.
    - Reflects widespread and frequent ENT conditions across all age groups.
3. Eyes
    - Nearly **2 million cases**.
    - Emphasizes the importance of **ophthalmologic care**, possibly including cataracts, vision correction, and screenings.
4. Brain
    - Around **1.3 million cases**.
    - Points to a strong volume in **neurology and neurosurgery**.
5. Cosmetic
    - Over **800K cases**, indicating **high elective demand** for aesthetic procedures.
6. Child Care
    - Close to Cosmetic in volume, showing ongoing focus on **pediatric care**.
7. Digestive
    - Over **600K cases**.
    - Suggests steady attention to **gastrointestinal health**.
8. Blood
    - Moderate volume (~400K), consistent with **hematology and related diagnostics**.
9. Dental
    - Slightly behind Blood.
    - Shows measurable demand for **oral health services**.
10. Cancer
    - Although lowest in this top 10, still significant.
    - May reflect data capture limits or separation into specific subspecialties (e.g., oncology types).

Age Profiling:

- Let's see the total of cases by age profile

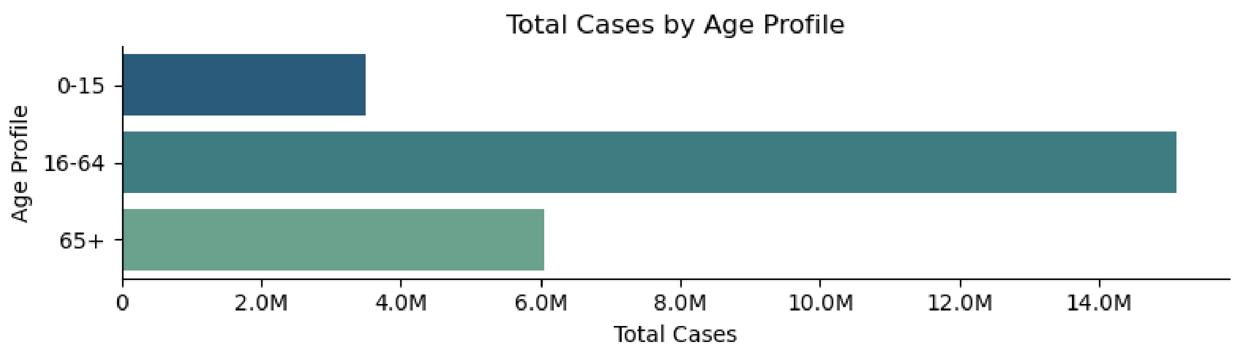
```
df['Age_Profile'].unique()
```

```
array(['16-64', '65+', '0-15', nan], dtype=object)
```

```
age_df = df.groupby('Age_Profile')['Total'].sum().reset_index()
age_df
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Age_Profile","rawType":"object","type":"string"},
{"name":"Total","rawType":"int64","type":"integer"}],"conversionMethod
":"pd.DataFrame","ref":"1adbdfd6-da23-4b71-bfa6-eb2c70ae4bd0","rows":
[["0","0-15","3502498"],["1","16-64","15095747"],
["2","65+","6039484"]],"shape":{"columns":2,"rows":3}}

```
plt.figure(figsize=(8, 2.4))
sns.barplot(
    data=age_df,
    y='Age_Profile',
    x='Total',
    palette='crest_r'
)

# formatting the xaxis values
plt.gca().xaxis.set_major_formatter(formatter)

plt.title('Total Cases by Age Profile')
plt.xlabel('Total Cases')
plt.ylabel('Age Profile')

sns.despine()
plt.tight_layout()
plt.show()
```



Overview

```
This horizontal bar chart breaks down healthcare cases across three
age groups:
```

- Age 16–64
  - Represents the **largest share**, with **over 15 million cases**.
  - Reflects the active working-age population, likely experiencing diverse healthcare needs: **occupational injuries, chronic conditions, elective surgeries**, and preventive care.
- Age 65+
  - Accounts for around **6 million cases**.
  - Indicative of an aging population with higher frequency of **chronic illnesses, surgeries, and specialist care** (e.g., cardiology, orthopedics).
- Age 0–15
  - The lowest volume at **under 4 million cases**.
  - Still a significant number, reflecting **pediatric care** needs such as vaccinations, respiratory conditions, and ENT issues.

Segment Insights:

- 1- Time Band vs Case Type:
  - Day Cases & Inpatient Cases.
  - Outpatient Cases.

```
df['Time_Bands'] = df['Time_Bands'].replace('18 Months +', '18+ Months')
df['Time_Bands'].unique()
```

```
array(['0-3 Months', '9-12 Months', '12-15 Months', '6-9 Months',
       '3-6 Months', '15-18 Months', '18+ Months', nan], dtype=object)
```

```
time_band_ordered = ['0-3 Months', '3-6 Months', '6-9 Months', '9-12 Months', '12-15 Months', '15-18 Months', '18+ Months']

time_band_df = df.groupby(['Time_Bands', 'Case_Type'])['Total'].sum().reset_index()
time_band_df.head()
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},{"name":"Time_Bands","rawType":"object","type":"string"},{"name":"Case_Type","rawType":"object","type":"string"},{"name":"Total","rawType":"int64","type":"integer"}],"conversionMethod":"pd.DataFrame","ref":"c7925701-5021-4e9a-a5b5-d89bc73e7a1f","rows":[["0","0-3 Months","Day Case","782718"],["1","0-3 Months","Inpatient","261174"],["2","0-3 Months","Outpatient","5940446"],["3","12-15 Months","Day Case","114064"],["4","12-15 Months","Inpatient","57880"]],"shape":{"columns":3,"rows":5}}

```
df_time_band_pivot = time_band_df.pivot(columns='Case_Type', index='Time_Bands', values='Total').reset_index()
df_time_band_pivot['Time_Bands'] = pd.Categorical(df_time_band_pivot['Time_Bands'], categories=time_band_ordered, ordered=True)
df_time_band_pivot.head(2)
```

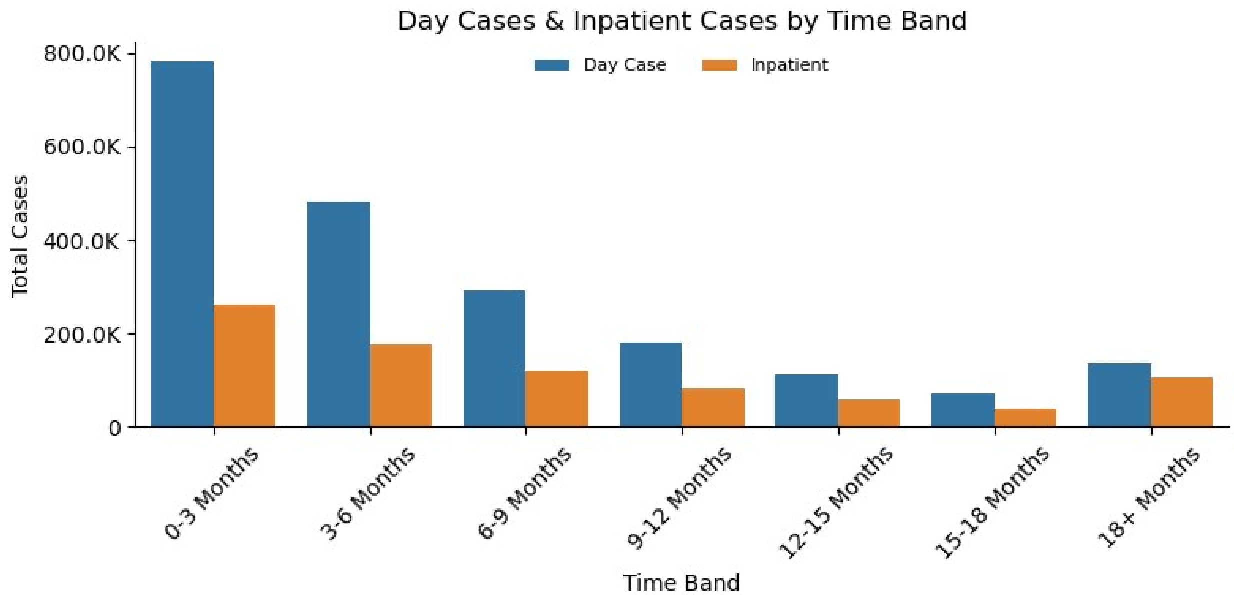
{"columns":[{"name":"index","rawType":"int64","type":"integer"},{"name":"Time_Bands","rawType":"category","type":"unknown"},{"name":"Day Case","rawType":"int64","type":"integer"},{"name":"Inpatient","rawType":"int64","type":"integer"},{"name":"Outpatient","rawType":"int64","type":"integer"}],"conversionMethod":"pd.DataFrame","ref":"39fd57d7-53a0-41a4-891a-626832b3da55","rows":[["0","0-3 Months","782718","261174","5940446"],["1","12-15 Months","114064","57880","1675924"]],"shape":{"columns":4,"rows":2}}

```
# df to be melted and reshaped for plotting
df_melted = df_time_band_pivot.melt(id_vars='Time_Bands',
```

```python
value_vars=df_time_band_pivot.columns[1:-1], # Exclude the first and last columns
                                    var_name='Case Type',
                                    value_name='Total Cases')

df_melted.head(2)
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Time_Bands","rawType":"category","type":"unknown"},
{"name":"Case Type","rawType":"object","type":"string"},{"name":"Total Cases","rawType":"int64","type":"integer"}],"conversionMethod":"pd.DataFrame","ref":"6160c37e-8d23-492a-8eb8-8252098d0f21","rows":[["0","0-3 Months","Day Case","782718"],["1","12-15 Months","Day Case","114064"]],"shape":{"columns":3,"rows":2}}

```python
plt.figure(figsize=(8, 4))
sns.barplot(
    data=df_melted,
    x='Time_Bands',
    y='Total Cases',
    hue='Case Type',
    palette='tab10'
)

plt.gca().yaxis.set_major_formatter(formatter)

plt.title('Day Cases & Inpatient Cases by Time Band')
plt.xlabel('Time Band')
plt.ylabel('Total Cases')
plt.xticks(rotation=45)
plt.legend(ncols=3, loc='upper center', framealpha=False, fontsize=8)

sns.despine()
plt.tight_layout()
plt.show()
```



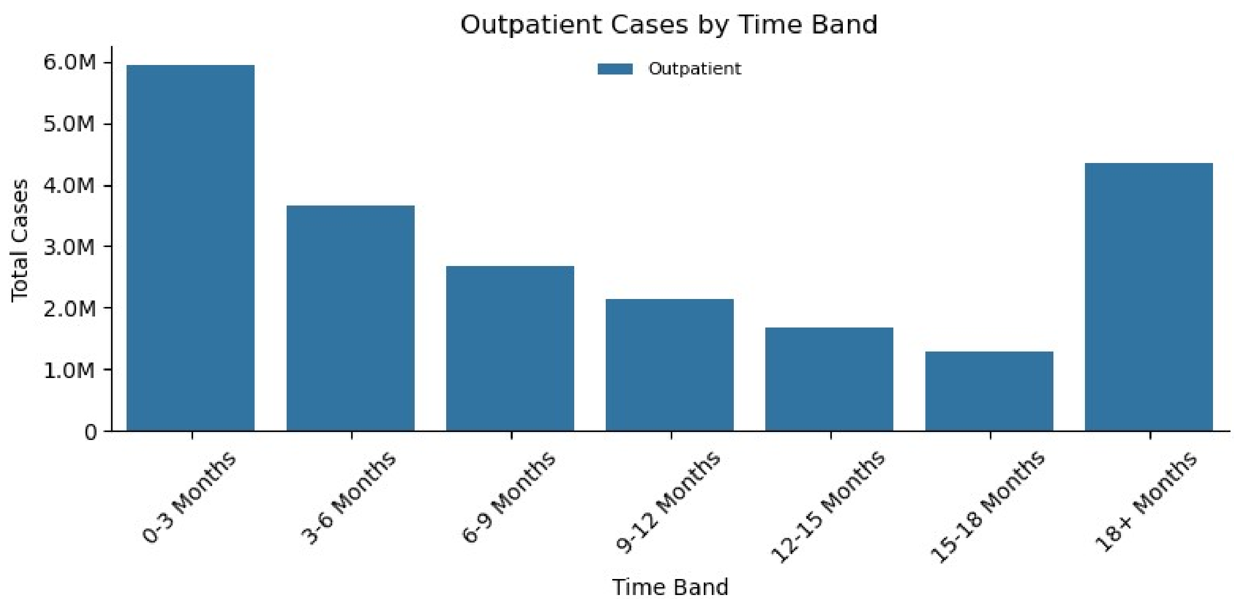
Insights:

- Early Treatment Dominance
  - **0–3 Months**: The majority of both **Day Cases (~800K)** and **Inpatients (~270K)** occur within this window.
  - Reflects **prompt access to care** post-referral, particularly for less complex treatments.
- Declining Trend Over Time
  - Both case types **decrease steadily** across subsequent time bands (3–6, 6–9, etc.).
  - Suggests that **delays in care** reduce case volume or possibly shift to long-term pathways.
- 18+ Months
  - A notable uptick in **both Day Case and Inpatient** cases is seen in the **18+ Months** band.
  - Indicates a **backlog or long-waiting patients**, which may require prioritization.

```
df_melted_outpatient = df_time_band_pivot.melt(id_vars='Time_Bands',

value_vars=df_time_band_pivot.columns[3:], # Exclude the first 3 columns
                                    var_name='Case Type',
                                    value_name='Total Cases')
df_melted_outpatient.head(2)
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},{"name":"Time_Bands","rawType":"category","type":"unknown"},{"name":"Case Type","rawType":"object","type":"string"},{"name":"Total Cases","rawType":"int64","type":"integer"}],"conversionMethod":"pd.DataFrame","ref":"2efb0199-0619-4600-ae41-798e08767ced","rows":[["0","0-3

```
Months","Outpatient","5940446"],["1","12-15
Months","Outpatient","1675924"]],"shape":{"columns":3,"rows":2}}

plt.figure(figsize=(8, 4))
sns.barplot(
    data=df_melted_outpatient,
    x='Time_Bands',
    y='Total Cases',
    hue='Case Type',
    palette='tab10'
)

plt.gca().yaxis.set_major_formatter(formatter)

plt.title('Outpatient Cases by Time Band')
plt.xlabel('Time Band')
plt.ylabel('Total Cases')
plt.xticks(rotation=45)
plt.legend(ncols=3, loc='upper center', framealpha=False, fontsize=8)

sns.despine()
plt.tight_layout()
plt.show()
```



Insights

- Strong Start
  - **0–3 Months** sees the **highest volume** (~6M cases), indicating strong early service responsiveness for outpatient care.
- Gradual Decline
  - There is a **steady drop** from **3–6 Months (~3.7M)** to **15–18 Months (~1.3M)**.

    - Suggests many patients are treated earlier in the timeline.
    - May reflect **effective triage or short-term needs** being prioritized.
- Noticeable Rise in 18+ Months
    - A significant **uptick (~4.3M cases)** occurs in the **18+ Months** band.
    - Implies a **backlog of long-waiting patients** or **deferred outpatient services**.
    - This echoes patterns seen in Day Case and Inpatient plots.

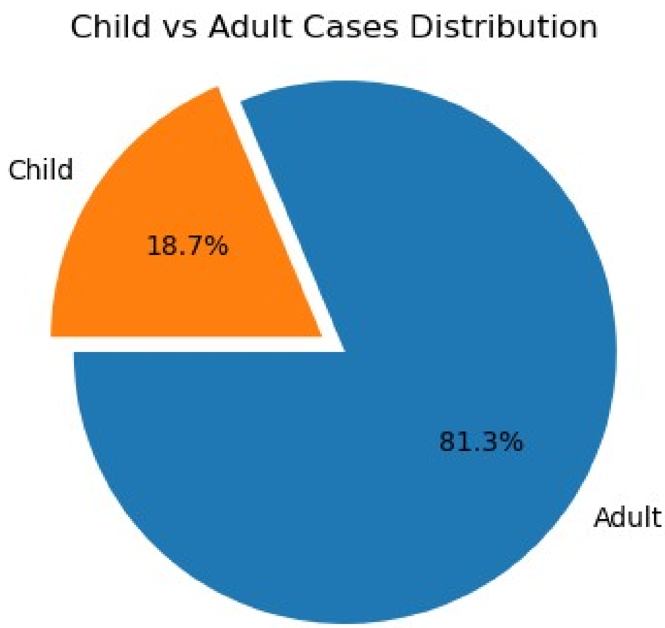
Segment Insights:

- 2- Adult vs Child Cases:

```
child_vs_adult =
df['Adult_Child'].value_counts().to_frame().reset_index()
child_vs_adult =
child_vs_adult[child_vs_adult['Adult_Child'].isin(['Adult', 'Child'])]

child_vs_adult
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Adult_Child","rawType":"object","type":"string"},
{"name":"count","rawType":"int64","type":"integer"}],"conversionMethod
":"pd.DataFrame","ref":"cd207f34-383e-4dbc-9c6c-1f3c3dd01657","rows":
[["0","Adult","368151"],["1","Child","84665"]],"shape":
{"columns":2,"rows":2}}

```
# Example explode if not defined already
explode = [0.05] * len(child_vs_adult)  # Slightly pop out all slices

plt.figure(figsize=(8, 4))

plt.pie(
    x=child_vs_adult['count'],
    labels=child_vs_adult['Adult_Child'],
    colors=sns.color_palette('tab10', n_colors=len(child_vs_adult)),
    autopct='%1.1f%%',
    startangle=180,
    explode=explode,
    textprops={'fontsize': 10}  # Optional: adjust font size
)

plt.title('Child vs Adult Cases Distribution', fontsize=12)
plt.axis('equal')  # equal aspect ratio ensures the pie is circular
plt.show()
```



Insights

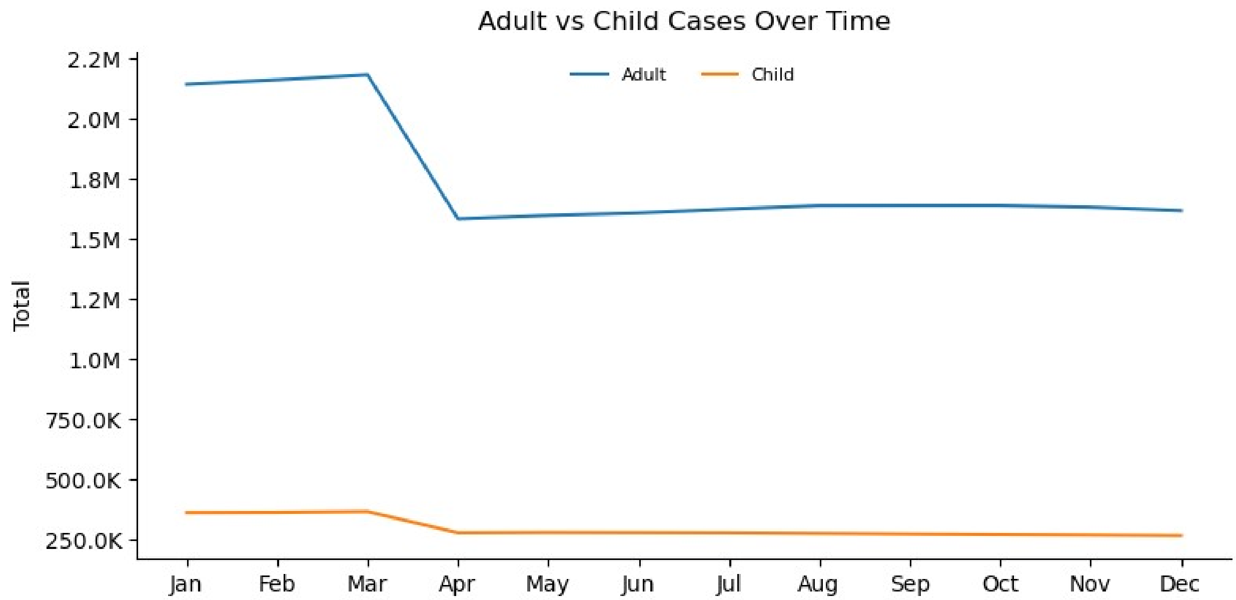
- Adult-Dominated Caseload - **Adults account for 81.3%** of total cases. - Reflects the **greater healthcare demand** from the adult population. - Likely influenced by chronic conditions, preventative care, and age-related needs.
- Child Segment - **Children make up 18.7%** of the cases. - Though smaller, this segment is still **significant**, especially for planning pediatric resources.

```
adult_vs_child_df = df.groupby(['Month_Name','Adult_Child'])
['Total'].sum()
adult_vs_child_df.dropna(inplace=True)
adult_vs_child_df = adult_vs_child_df.reset_index()
adult_vs_child_df['Month_Name'] =
adult_vs_child_df['Month_Name'].str[:3] # to abbreviate the month name
to the first 3 letters
adult_vs_child_df['Month_Name'] =
pd.Categorical(adult_vs_child_df['Month_Name'],
categories=month_order, ordered=True)
adult_vs_child_df =
adult_vs_child_df[adult_vs_child_df['Adult_Child'].isin(['Adult',
'Child'])]
adult_vs_child_df
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Month_Name","rawType":"category","type":"unknown"},
{"name":"Adult_Child","rawType":"object","type":"string"},

```
{"name":"Total","rawType":"int64","type":"integer"}],"conversionMethod
":"pd.DataFrame","ref":"6cf2de34-9554-40e4-84c6-eaebeb6054ae","rows":
[["1","Apr","Adult","1584460"],["2","Apr","Child","278210"],
["4","Aug","Adult","1639213"],["5","Aug","Child","275741"],
["7","Dec","Adult","1618434"],["8","Dec","Child","266412"],
["10","Feb","Adult","2162622"],["11","Feb","Child","363126"],
["13","Jan","Adult","2144065"],["14","Jan","Child","362021"],
["16","Jul","Adult","1624564"],["17","Jul","Child","278142"],
["19","Jun","Adult","1608703"],["20","Jun","Child","278977"],
["22","Mar","Adult","2183517"],["23","Mar","Child","366420"],
["25","May","Adult","1598515"],["26","May","Child","279671"],
["28","Nov","Adult","1632575"],["29","Nov","Child","268931"],
["31","Oct","Adult","1639747"],["32","Oct","Child","270878"],
["34","Sep","Adult","1639662"],["35","Sep","Child","273123"]],"shape":
{"columns":3,"rows":24}}
```


```
plt.figure(figsize=(8, 4))
sns.lineplot(
    data=adult_vs_child_df,
    x='Month_Name',
    y='Total',
    hue='Adult_Child',
    palette='tab10'
)

plt.gca().yaxis.set_major_formatter(formatter)

plt.title('Adult vs Child Cases Over Time', pad=10)
plt.xlabel('')

plt.legend(ncols=2, loc='upper center', framealpha=False, fontsize=8)

sns.despine()
plt.tight_layout()
plt.show()
```



Insights

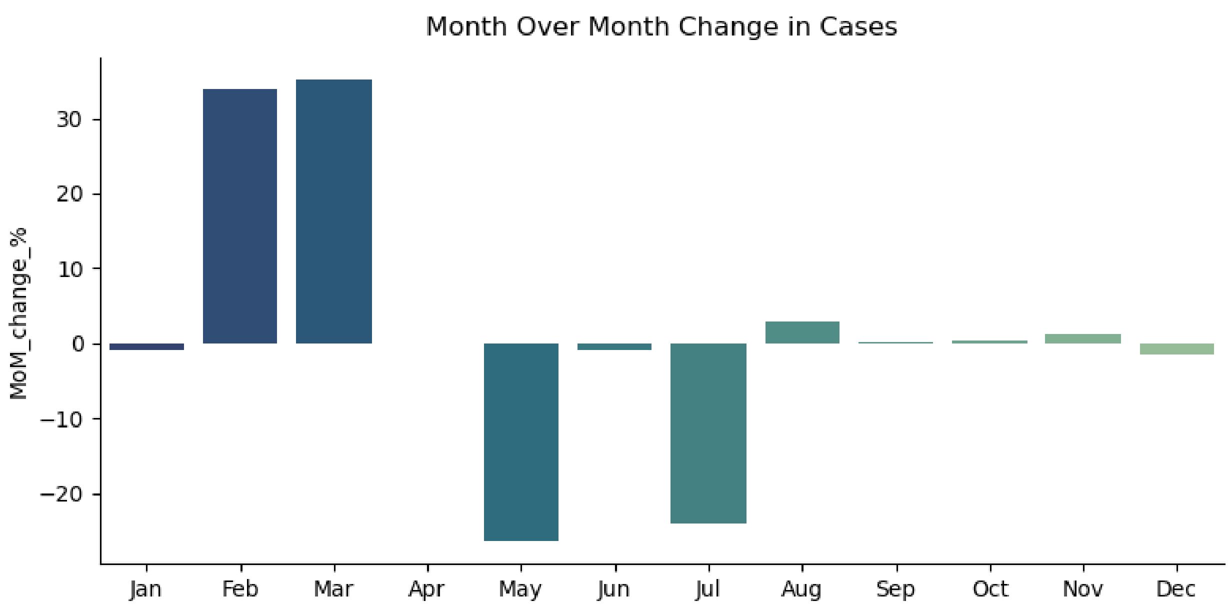
- Adult Cases:
  - **Consistently higher** volume throughout the year.
  - **Notable drop in April** (~2.15M → ~1.65M cases).
    - May suggest seasonal trends, system delays, or reporting lags.
  - From May to December, volumes remain **stable with slight fluctuation** around ~1.7M.
- Child Cases:
  - Relatively **flat and stable**, hovering just under **300K per month**.
  - A dip observed in **April**, mirroring adult trend, though less dramatic.

Month over Month (MoM) &Year over Year (YoY) % Change in Cases:

- Let's create a Monthly Summary:
  - We'll sum Total per month, so we can compare either month-over-month or year-over-year:

```
monthly_cases = df.groupby('Month_Name')['Total'].sum().reset_index()

# Calculate the percentage change month-over-month
monthly_cases['MoM_change_%'] = (monthly_cases['Total'].pct_change() * 
100 ).round(2)
monthly_cases['MoM_change_%'] = monthly_cases['MoM_change_
%'].fillna(0)  # Fill NaN values with 0 for the first month
monthly_cases['Month_Name'] = monthly_cases['Month_Name'].str[:3] # to 
abbreviate the month name to the first 3 letters
# month_order was defined earlier in the code
# here you can categorise and order Month_Name to plot
monthly_cases['Month_Name'] = 
```

```
pd.Categorical(monthly_cases['Month_Name'], categories=month_order,
ordered=True)

plt.figure(figsize=(8, 4))
sns.barplot(
    data=monthly_cases,
    x='Month_Name',
    y='MoM_change_%',
    palette='crest_r'
)

plt.title('Month Over Month Change in Cases', pad=10)
plt.xlabel('')

sns.despine()
plt.tight_layout()
plt.show()
```



Month-Over-Month (MoM) Change in Total Cases

- This bar chart shows the **percentage change in total cases** compared to the previous month.
- **February & March**:
  - Over **+30% growth** each month.
  - Indicates a **sharp surge in cases** during late Q1.
- **May & July**:
  - **-25%** MoM drop in both months.

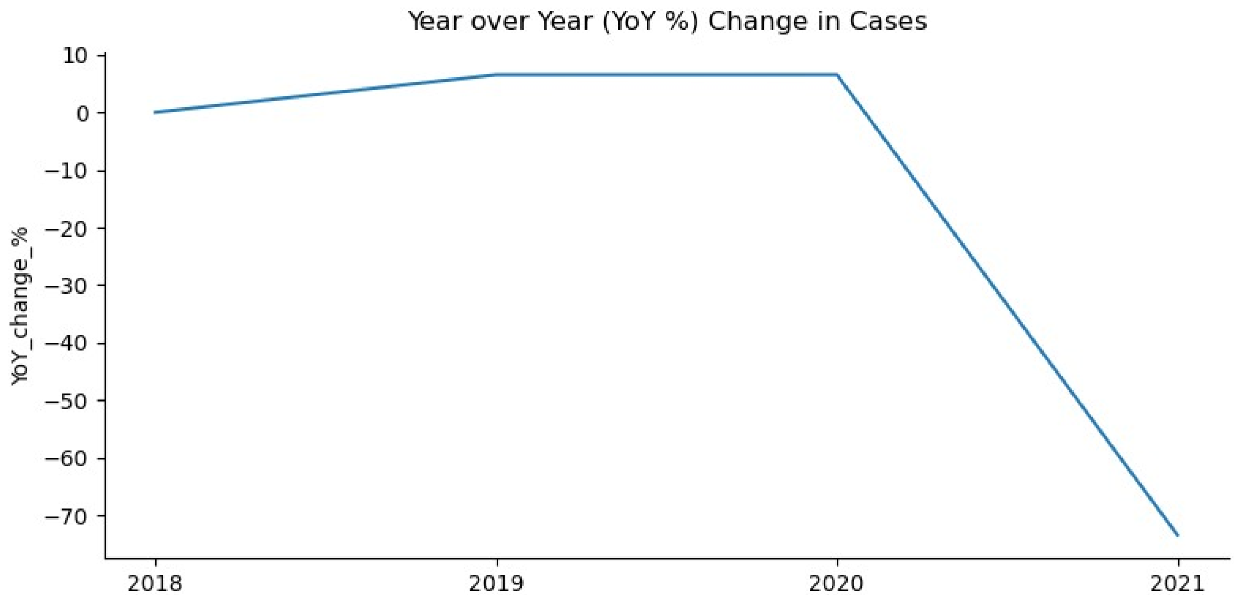
- Possibly due to system delays, seasonal effects, or fewer operational days.

- **August–December**:
  - Fluctuations become **minimal**, mostly between **-2% and +3%**.
  - Suggests a **steady state** of case volume entering the final quarter.

```
yearly_cases = df.groupby('Year')['Total'].sum().reset_index()
yearly_cases['YoY_change_%'] = (yearly_cases['Total'].pct_change() *
100 ).round(2)
yearly_cases['Year'] = yearly_cases['Year'].astype(str)  # Convert
Year to string for better x-axis labels
yearly_cases['YoY_change_%'] = yearly_cases['YoY_change_%'].fillna(0)
# Fill NaN values with 0 for the first year


yearly_cases
```

{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Year","rawType":"object","type":"string"},
{"name":"Total","rawType":"int64","type":"integer"},
{"name":"YoY_change_
%","rawType":"float64","type":"float"}],"conversionMethod":"pd.DataFra
me","ref":"2deb65a0-3a47-4c72-8e51-2fd17a07fe60","rows":
[["0","2018","7036731","0.0"],["1","2019","7495574","6.52"],
["2","2020","7984923","6.53"],["3","2021","2120979","-
73.44"]],"shape":{"columns":3,"rows":4}}

```
plt.figure(figsize=(8, 4))
sns.lineplot(
    data=yearly_cases,
    x='Year',
    y='YoY_change_%',
    palette='crest_r'
)

plt.title('Year over Year (YoY %) Change in Cases', pad=10)
plt.xlabel('')

sns.despine()
plt.tight_layout()
plt.show()
```



Insights**

- **General Trend**
  - The YoY percentage change in cases starts at a relatively stable level around **0%** in 2018.
  - From 2018 to 2019, there is a slight increase, reaching a peak of approximately **+10%** in 2019.
  - In 2020, the trend reverses sharply, with a significant decline in the YoY percentage change.
  - By 2021, the YoY percentage change drops dramatically to around **-70%**, indicating a substantial decrease in cases compared to the previous year.
- **Key Observations**
  - **Peak Growth in 2019**: The positive growth of about **+10%** indicates a notable increase in cases compared to the previous year.
  - **Sharp Decline in 2020**: The transition from a positive to a negative percentage change signifies a sudden drop in cases. This could be attributed to external factors such as changes in reporting, interventions, or other contextual events.
  - **Dramatic Drop in 2021**: The steep decline to **-70%** highlights an unprecedented reduction in cases compared to 2020. This could reflect the impact of measures like lockdowns, vaccinations, or behavioral changes.

Conclusion

This analysis provided valuable insights into healthcare case trends across specialties, age groups, and time periods. Key highlights include:

- **Outpatient cases dominate**, underlining the importance of non-admitted care services.
- **Cardiology** and other high-volume specialties require focused resource planning.
- The **adult population accounts for over 80%** of cases, emphasizing the need for adult-focused healthcare services.

- A significant **YoY decline in 2021** points to external impacts such as global health events or policy changes.

Overall, this project demonstrates the power of exploratory data analysis in uncovering patterns, supporting data-driven decisions, and improving healthcare delivery systems.

Prepared by : Mohamed Fawzi.

E-mail : modyreturn@gmail.com

Github : https://github.com/modyreturn

Linkedin : www.linkedin.com/in/mofawzirj