```
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

```
# 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
```

```python
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)
```

Exploratory Data Analysis (EDA):

Statistic Summary

```python
# 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"}],"conversion
Method":"pd.DataFrame","ref":"ae655ce2-f096-4212-a8b2-
7e07f9d77d66","rows":
[["count","452991","452800.0","452991","452991","452816","452989","452
991.0","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","766
14",null,"47110"],["mean","2019-09-09
18:57:46.892720640","2619.1445759717312",null,null,null,null,"54.39005
852213399",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",nul
l],
["std",null,"2362.043475185623",null,null,null,null,"120.7928371221548
",null,null,"0.9635806573834385",null]],"shape":
{"columns":11,"rows":11}}
```

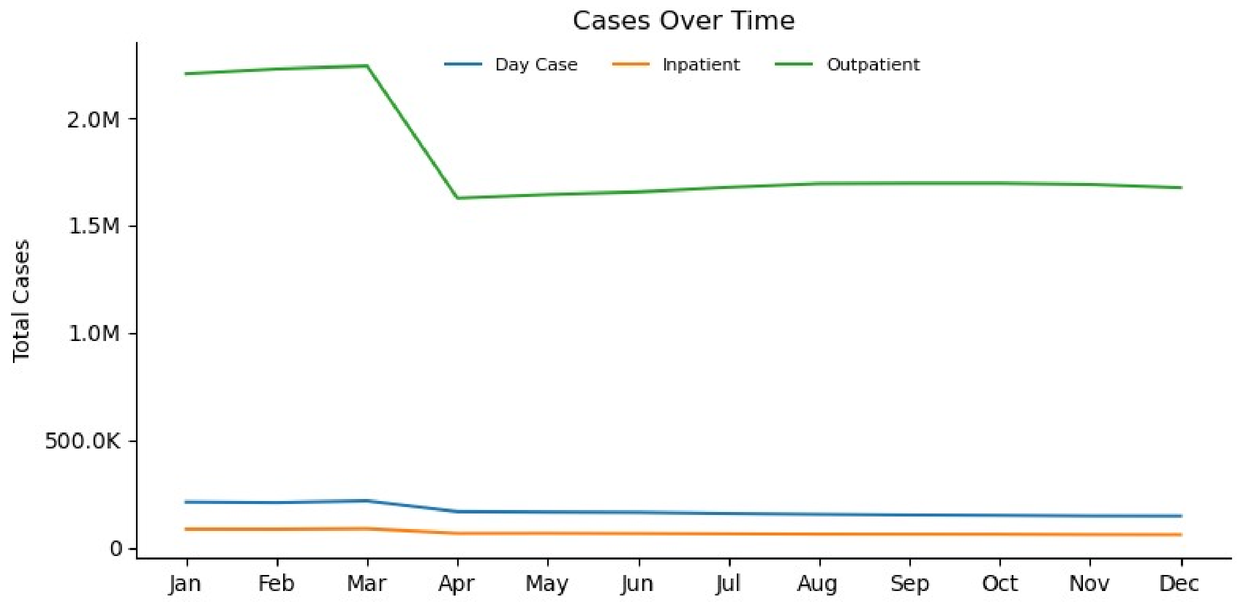
Cases Over Time:

- 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.

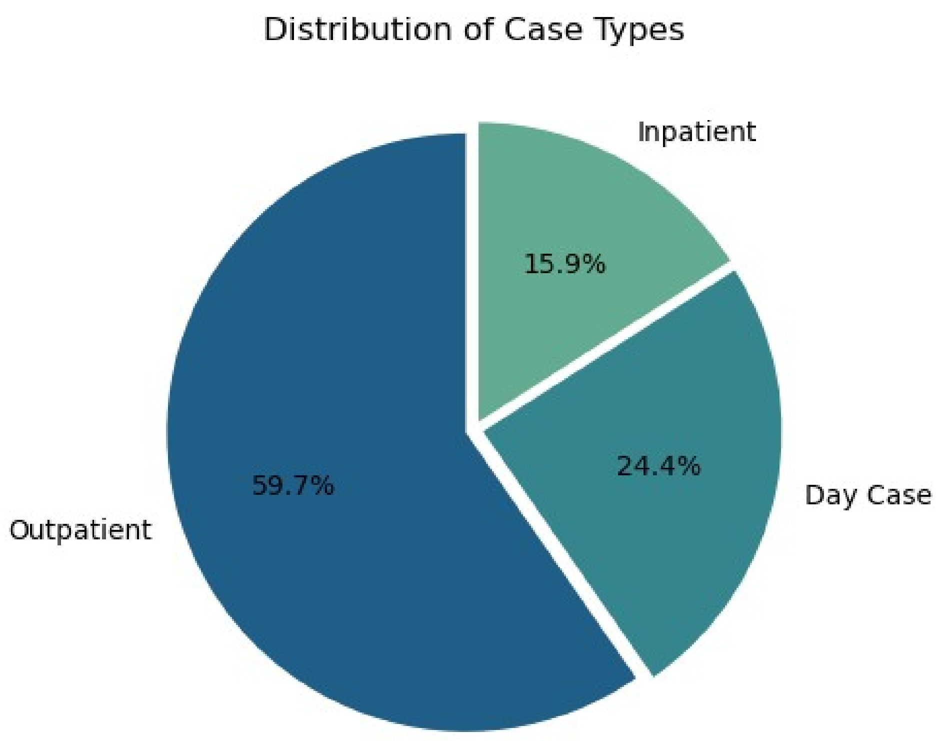
Cases Type Distributions:

- 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.

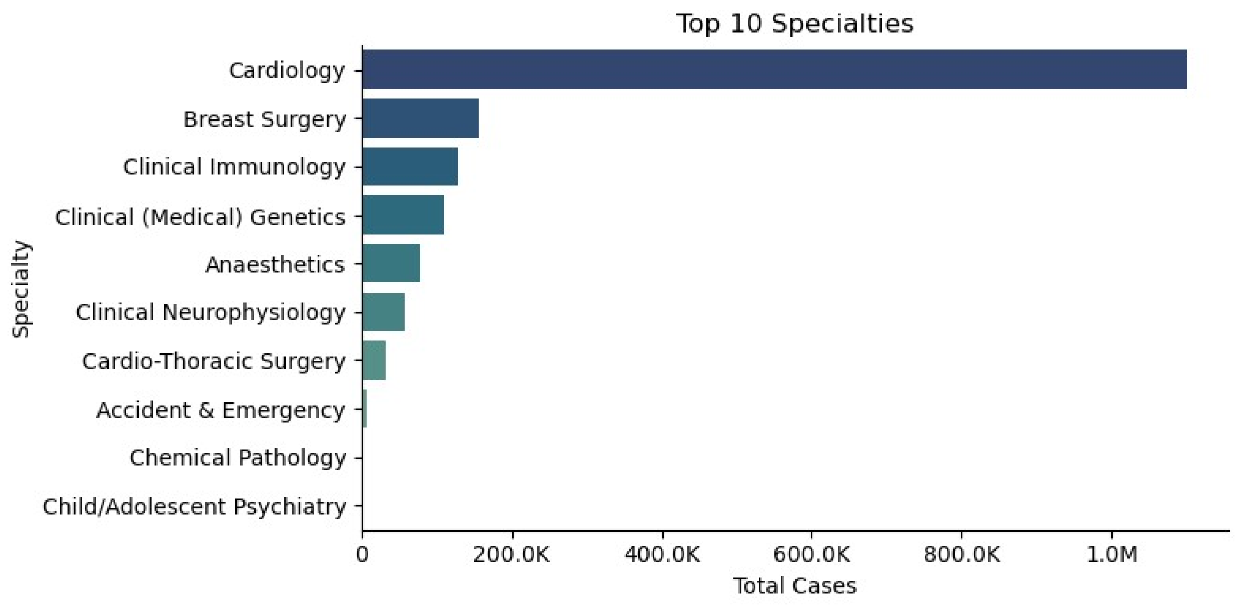
Specialty Analysis:

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

```
#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}}

```
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()
```



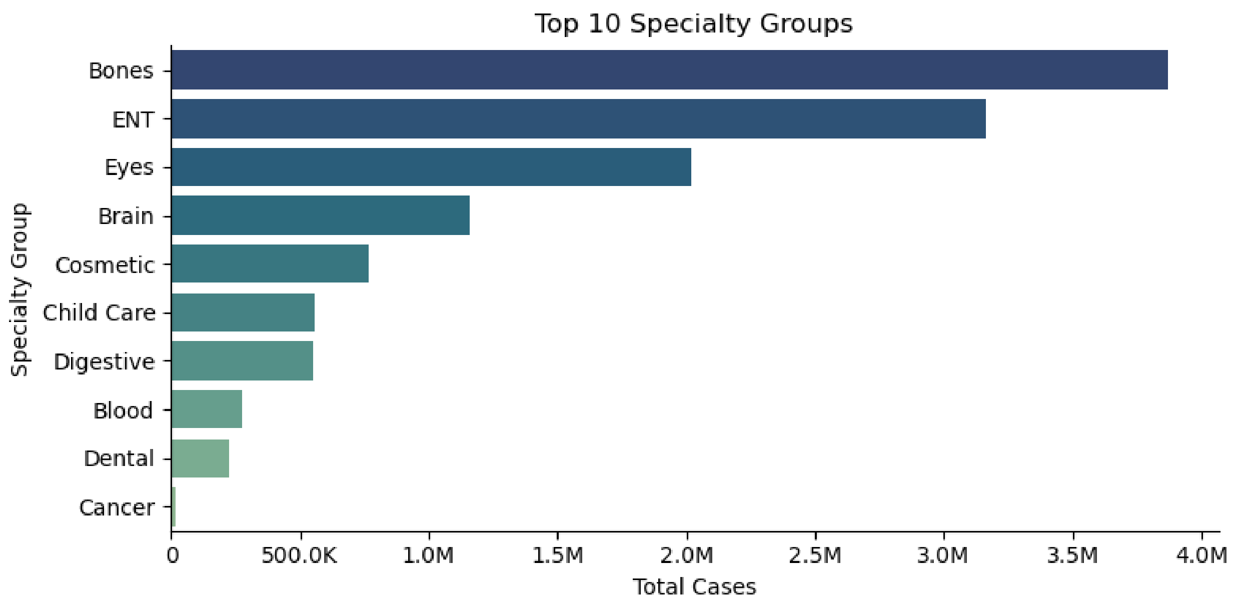
Key Insights

- 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

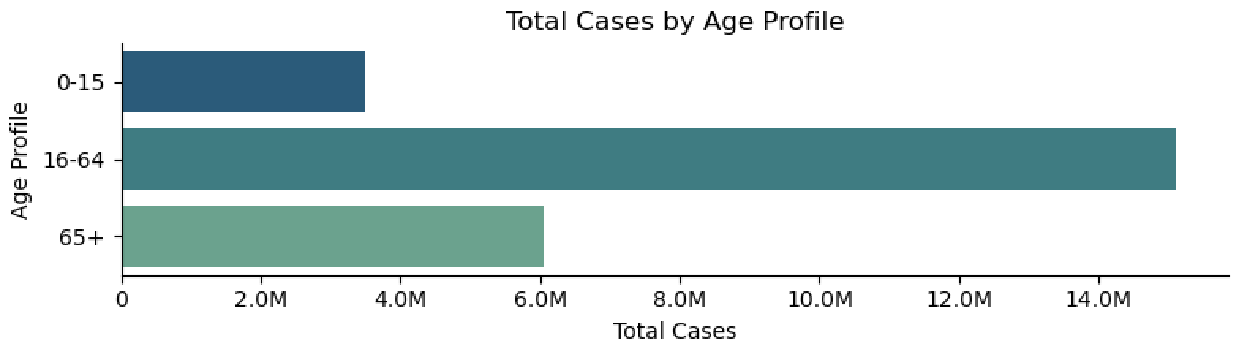
```
df['Age_Profile'].unique()
```

```
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}}

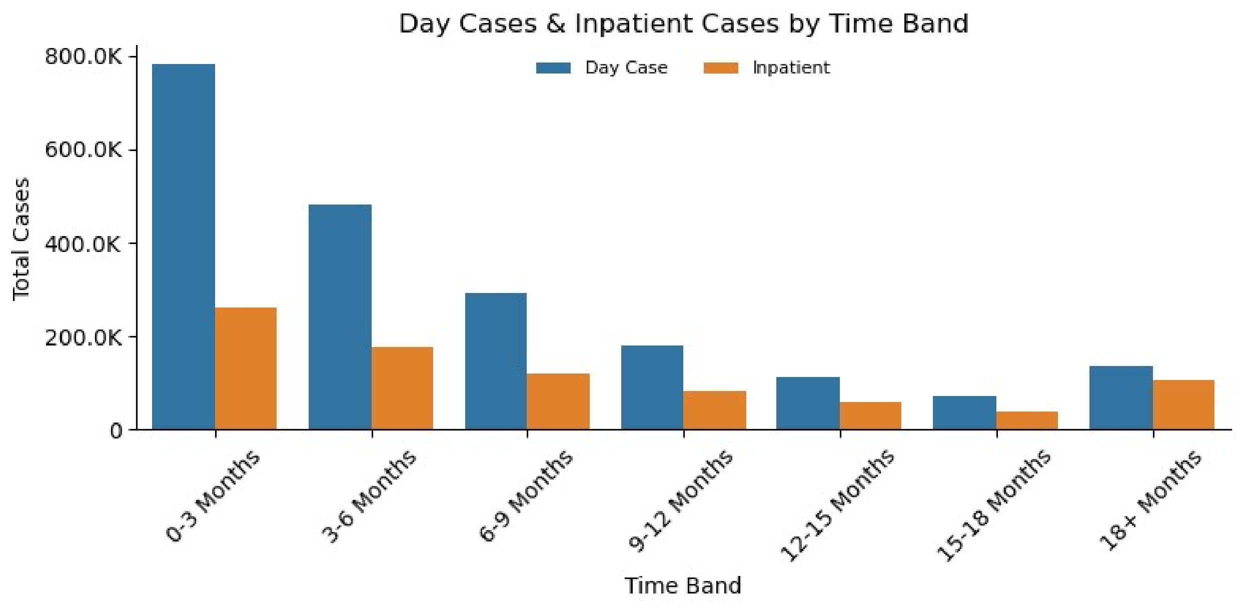
```
df_time_band_pivot = time_band_df.pivot(columns='Case_Type',
index='Time_Bands', values='Total').reset_index()
df_time_band_pivot['Time_Bands'] =
pd.Categorical(df_time_band_pivot['Time_Bands'],
categories=time_band_ordered, ordered=True)
df_time_band_pivot.head(2)
```

{"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"}],"conversionM
ethod":"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',
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.Dat
aFrame","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}}

```
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()
```



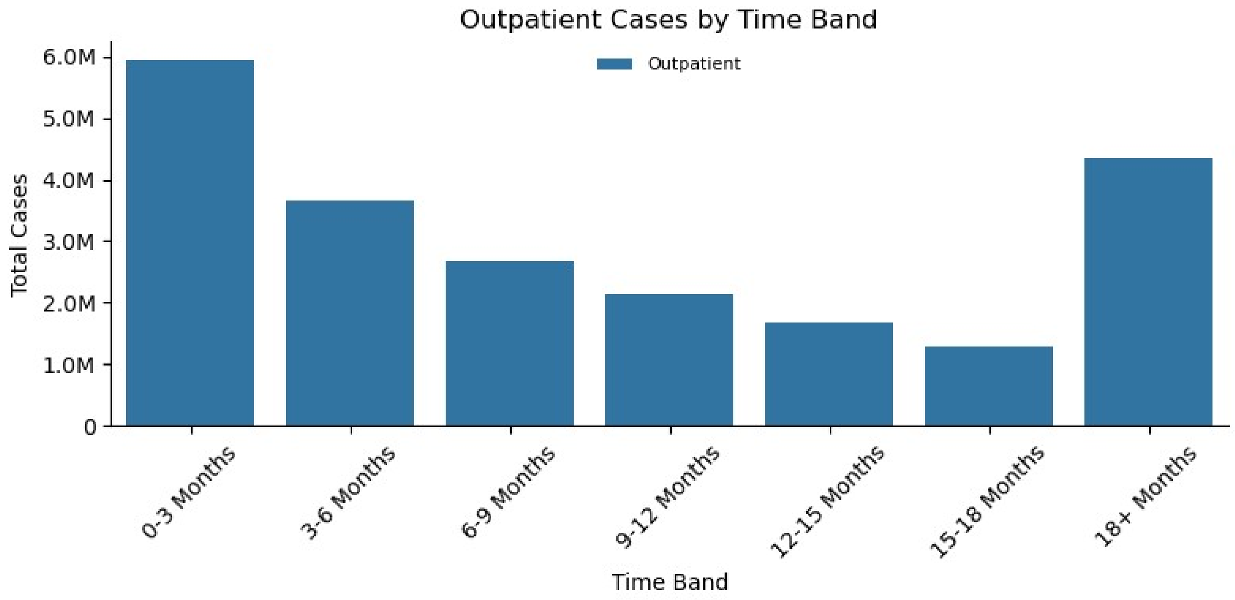
Insights:

- 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.Dat
aFrame","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.

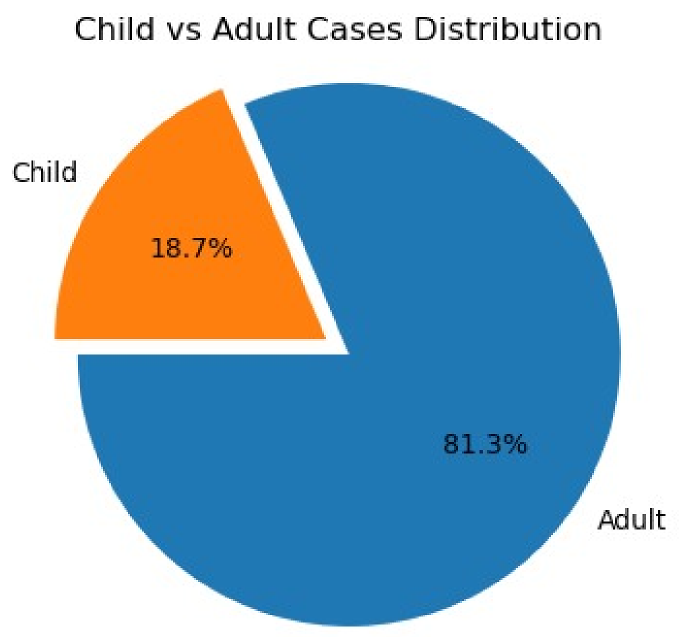
Segment Insights:

- 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"},
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{"name":"Adult_Child","rawType":"object","type":"string"},

```
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["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}}
```

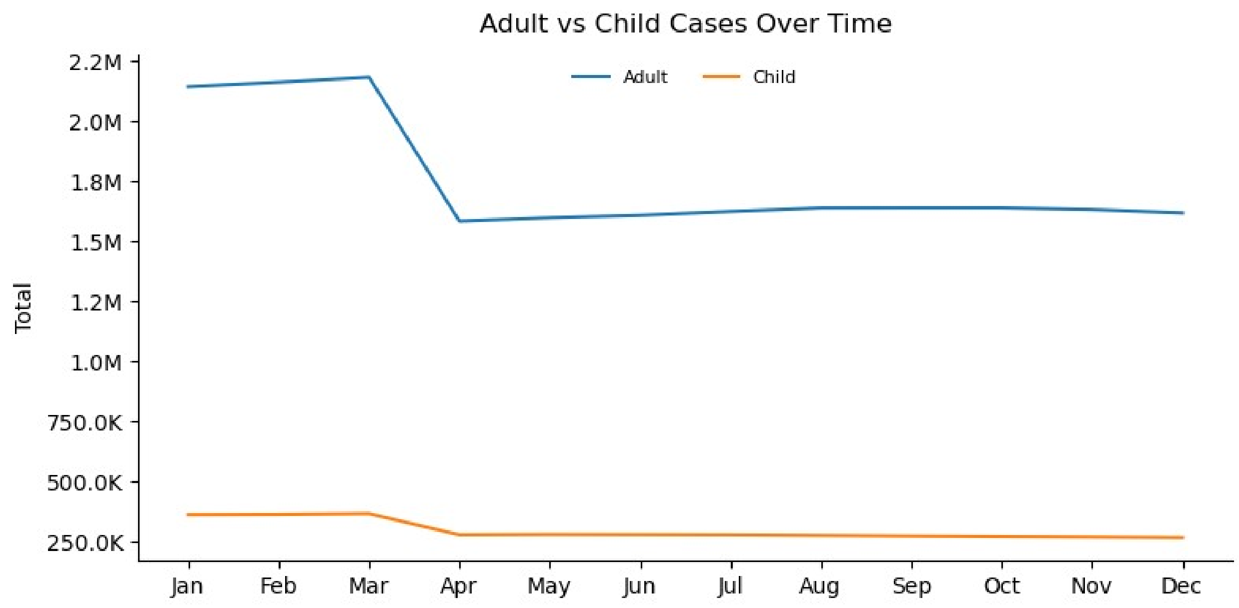
```
plt.figure(figsize=(8, 4))
sns.lineplot(
    data=adult_vs_child_df,
    x='Month_Name',
    y='Total',
    hue='Adult_Child',
    palette='tab10'
)

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:

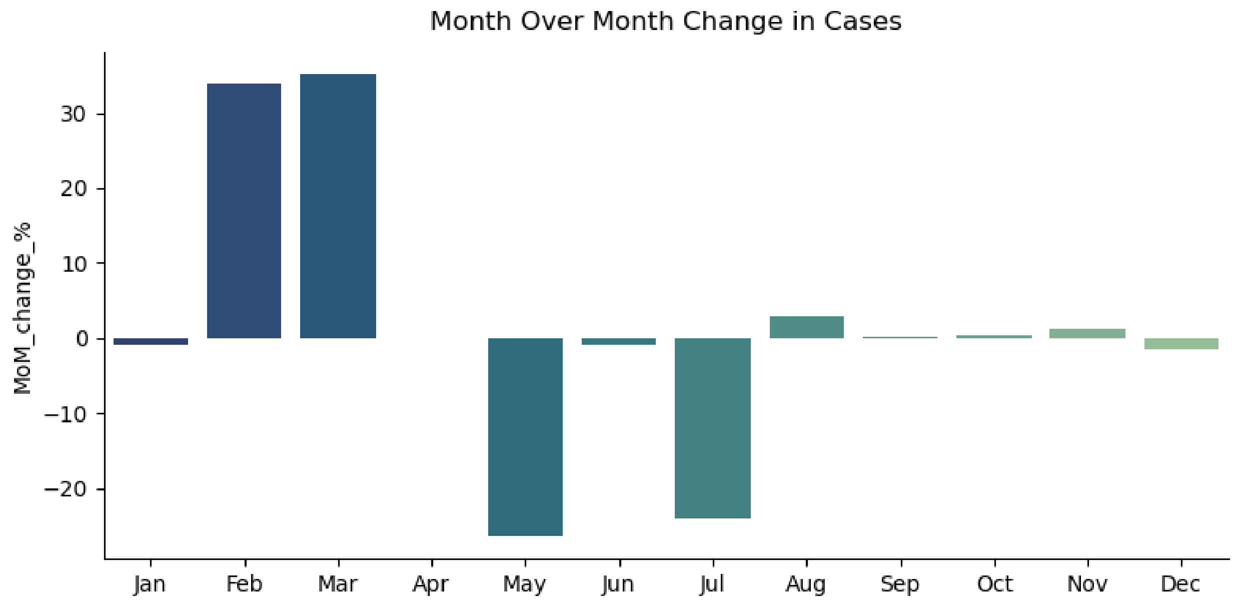
```
monthly_cases = df.groupby('Month_Name')['Total'].sum().reset_index()

# 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"},
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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}}
```
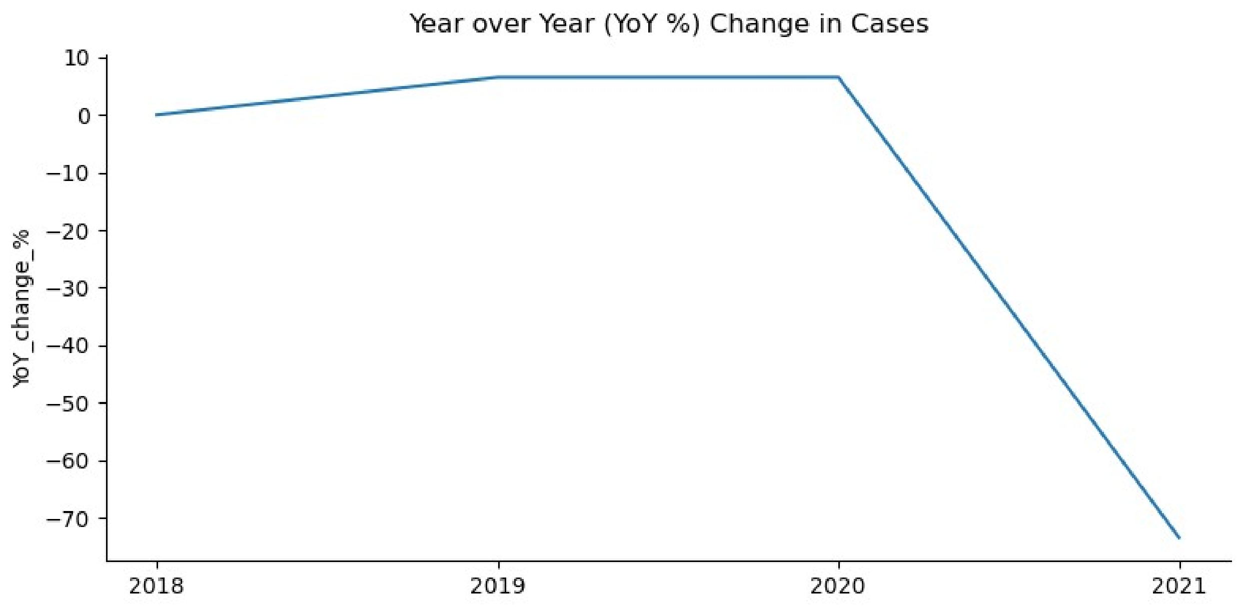

```
plt.figure(figsize=(8, 4))
sns.lineplot(
    data=yearly_cases,
    x='Year',
    y='YoY_change_%',
    palette='crest_r'
)

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.