

# 250k Medicines Usage, Side Effects and Substitutes

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## 1 About Me

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```
[348]: import pandas as pd
```

## 2 Importing Dataset and Checking Basic Info

```
[349]: fname = "250k Medicines Usage, Side Effects and Substitutes.csv"
raw_data = pd.read_csv(fname)
df= raw_data.copy()
df.head()
```

```
C:\Users\Mohammed Riad\AppData\Local\Temp\ipykernel_14468\1691797094.py:2:
DtypeWarning: Columns (42,43,44,45,46,47,48) have mixed types. Specify dtype
option on import or set low_memory=False.
raw_data = pd.read_csv(fname)
```

```
[349]:
```

	id	name	substitute0	\
0	1	augmentin 625 duo tablet	Penciclav 500 mg/125 mg Tablet	
1	2	azithral 500 tablet	Zithrocare 500mg Tablet	
2	3	ascoril ls syrup	Solvin LS Syrup	
3	4	allegra 120mg tablet	Lcfex Tablet	
4	5	avil 25 tablet	Eralet 25mg Tablet	

	substitute1	substitute2	substitute3	\
0	Moxikind-CV 625 Tablet	Moxiforce-CV 625 Tablet	Fightox 625 Tablet	
1	Azax 500 Tablet	Zady 500 Tablet	Cazithro 500mg Tablet	
2	Ambrodil-LX Syrup	Zerotuss XP Syrup	Capex LS Syrup	
3	Etofex 120mg Tablet	Nexofex 120mg Tablet	Fexise 120mg Tablet	
4	NaN	NaN	NaN	

	substitute4	sideEffect0	sideEffect1	sideEffect2	...	\
0	Novamox CV 625mg Tablet	Vomiting	Nausea	Diarrhea	...	

1	Trulimax 500mg Tablet	Vomiting	Nausea	Abdominal pain	...
2	Broxum LS Syrup	Nausea	Vomiting	Diarrhea	...
3	Histafree 120 Tablet	Headache	Drowsiness	Dizziness	...
4	NaN	Sleepiness	Dryness in mouth	NaN	...

	sideEffect41		use0	\
0	NaN	Treatment of Bacterial infections		
1	NaN	Treatment of Bacterial infections		
2	NaN	Treatment of Cough with mucus		
3	NaN	Treatment of Sneezing and runny nose due to al...		
4	NaN	Treatment of Allergic conditions		

		use1	use2	use3	use4	\
0		NaN	NaN	NaN	NaN	
1		NaN	NaN	NaN	NaN	
2		NaN	NaN	NaN	NaN	
3	Treatment of Allergic conditions	NaN	NaN	NaN		
4		NaN	NaN	NaN	NaN	

		Chemical Class	Habit Forming	Therapeutic Class	\
0		NaN	No	ANTI INFECTIVES	
1		Macrolides	No	ANTI INFECTIVES	
2		NaN	No	RESPIRATORY	
3	Diphenylmethane Derivative		No	RESPIRATORY	
4	Pyridines Derivatives		No	RESPIRATORY	

		Action Class
0		NaN
1		Macrolides
2		NaN
3	H1 Antihistaminics (second Generation)	
4	H1 Antihistaminics (First Generation)	

[5 rows x 58 columns]

[350]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 248218 entries, 0 to 248217
Data columns (total 58 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    248218 non-null int64
1   name                  248218 non-null object
2   substitute0           238621 non-null object
3   substitute1           233867 non-null object
4   substitute2           230233 non-null object
5   substitute3           226856 non-null object
```

6	substitute4	223962 non-null	object
7	sideEffect0	248218 non-null	object
8	sideEffect1	238416 non-null	object
9	sideEffect2	229500 non-null	object
10	sideEffect3	207638 non-null	object
11	sideEffect4	163560 non-null	object
12	sideEffect5	131258 non-null	object
13	sideEffect6	91857 non-null	object
14	sideEffect7	67750 non-null	object
15	sideEffect8	48506 non-null	object
16	sideEffect9	37708 non-null	object
17	sideEffect10	27274 non-null	object
18	sideEffect11	20331 non-null	object
19	sideEffect12	16282 non-null	object
20	sideEffect13	14727 non-null	object
21	sideEffect14	10419 non-null	object
22	sideEffect15	7681 non-null	object
23	sideEffect16	6009 non-null	object
24	sideEffect17	5382 non-null	object
25	sideEffect18	4515 non-null	object
26	sideEffect19	3946 non-null	object
27	sideEffect20	3223 non-null	object
28	sideEffect21	3125 non-null	object
29	sideEffect22	3048 non-null	object
30	sideEffect23	2905 non-null	object
31	sideEffect24	2723 non-null	object
32	sideEffect25	1503 non-null	object
33	sideEffect26	1503 non-null	object
34	sideEffect27	1494 non-null	object
35	sideEffect28	1494 non-null	object
36	sideEffect29	1438 non-null	object
37	sideEffect30	1329 non-null	object
38	sideEffect31	1329 non-null	object
39	sideEffect32	1328 non-null	object
40	sideEffect33	1169 non-null	object
41	sideEffect34	1166 non-null	object
42	sideEffect35	2 non-null	object
43	sideEffect36	2 non-null	object
44	sideEffect37	2 non-null	object
45	sideEffect38	2 non-null	object
46	sideEffect39	2 non-null	object
47	sideEffect40	2 non-null	object
48	sideEffect41	2 non-null	object
49	use0	248218 non-null	object
50	use1	73365 non-null	object
51	use2	28307 non-null	object
52	use3	7379 non-null	object
53	use4	4971 non-null	object

```

54 Chemical Class      137791 non-null object
55 Habit Forming       248218 non-null object
56 Therapeutic Class   248149 non-null object
57 Action Class        138036 non-null object
dtypes: int64(1), object(57)
memory usage: 109.8+ MB

```

This Dataset Has Total 58 columns.It has

```

-5 substitutes columnns
-42 sideeffects columnns
-5 uses columnns
-and 4 class columnns

```

### 3 Data Cleaning And Processing

#### 3.0.1 Dropping Unneccessary column

```

[351]: df = df.drop("id",axis =1)
df.head()

```

```

[351]:
      name      substitute0 \
0 augmentin 625 duo tablet  Penciclav 500 mg/125 mg Tablet
1      azithral 500 tablet      Zithrocare 500mg Tablet
2      ascoril ls syrup      Solvin LS Syrup
3      allegra 120mg tablet      Lcfex Tablet
4      avil 25 tablet      Eralet 25mg Tablet

      substitute1      substitute2      substitute3 \
0 Moxikind-CV 625 Tablet  Moxiforce-CV 625 Tablet  Fightox 625 Tablet
1      Azax 500 Tablet      Zady 500 Tablet  Cazithro 500mg Tablet
2      Ambrodil-LX Syrup      Zerotuss XP Syrup      Capex LS Syrup
3      Etofex 120mg Tablet      Nexofex 120mg Tablet      Fexise 120mg Tablet
4      NaN      NaN      NaN

      substitute4 sideEffect0      sideEffect1      sideEffect2 \
0 Novamox CV 625mg Tablet  Vomiting      Nausea      Diarrhea
1      Trulimax 500mg Tablet  Vomiting      Nausea  Abdominal pain
2      Broxum LS Syrup      Nausea      Vomiting      Diarrhea
3      Histafree 120 Tablet  Headache      Drowsiness      Dizziness
4      NaN  Sleepiness  Dryness in mouth      NaN

      sideEffect3 ... sideEffect41 \
0      NaN ...      NaN
1      Diarrhea ...      NaN
2  Upset stomach ...      NaN
3      Nausea ...      NaN
4      NaN ...      NaN

```

```

                                use0 \
0      Treatment of Bacterial infections
1      Treatment of Bacterial infections
2      Treatment of Cough with mucus
3  Treatment of Sneezing and runny nose due to al...
4      Treatment of Allergic conditions

                                use1 use2 use3 use4 \
0      NaN NaN NaN NaN
1      NaN NaN NaN NaN
2      NaN NaN NaN NaN
3  Treatment of Allergic conditions NaN NaN NaN
4      NaN NaN NaN NaN

      Chemical Class Habit Forming Therapeutic Class \
0      NaN NaN No ANTI INFECTIVES
1      Macrolides NaN No ANTI INFECTIVES
2      NaN NaN No RESPIRATORY
3  Diphenylmethane Derivative NaN No RESPIRATORY
4      Pyridines Derivatives NaN No RESPIRATORY

      Action Class
0      NaN
1      Macrolides
2      NaN
3  H1 Antihistaminics (second Generation)
4  H1 Antihistaminics (First Generation)

[5 rows x 57 columns]

```

### 3.0.2 Dropping Duplicated Rows across all the columns

```
[352]: df.duplicated().any()
```

```
[352]: True
```

```
[353]: # Drop duplicated rows, keeping only the first occurrence
df = df.drop_duplicates()
#checking again is there any duplicated rows after deletion
df.duplicated().any()
```

```
[353]: False
```

### 3.0.3 Working With Missing Values

```
[354]: df.isnull().sum().head()
```

```
[354]: name          0
      substitute0    8820
      substitute1   13196
      substitute2   16574
      substitute3   19692
      dtype: int64
```

```
[355]: #making a dataframe with the missing values of the dataset

null_counts = df.isnull().sum()
missing_value = pd.DataFrame(null_counts, columns=['null_count']).reset_index()
missing_value = missing_value.rename(columns={'index': 'Column'})

# Drop the first two row namem,as name has no missing value
missing_value = missing_value.drop([0]).reset_index(drop=True)

missing_value.head()
```

```
[355]:      Column  null_count
0  substitute0      8820
1  substitute1     13196
2  substitute2     16574
3  substitute3     19692
4  substitute4     22357
```

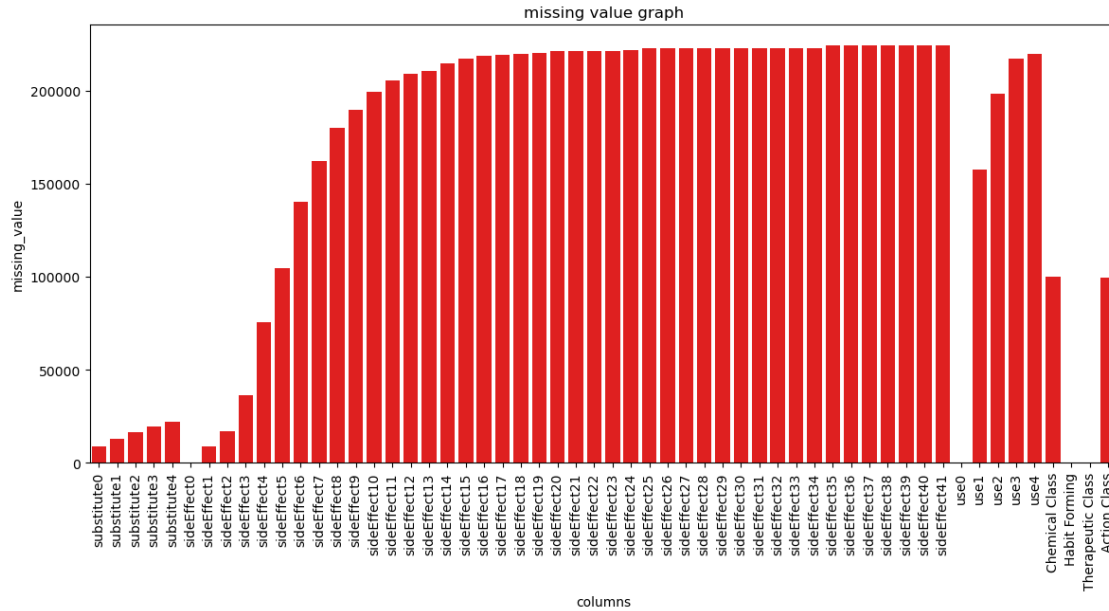
```
[356]: #creating a barplot with the missing value

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(14, 6))
sns.barplot(x='Column', y='null_count', data=missing_value, color='red')

plt.xlabel('columns')
plt.ylabel('missing_value')
plt.title("missing value graph")
plt.xticks(rotation=90) # Rotate x-axis labels if necessary
plt.show()

# Show the plot
plt.show()
```



```
[357]: #filling the missing values with unknown
df.fillna("UnKnown",inplace = True)

#checking is there any missing value remaining
df.isnull().sum()
```

```
[357]: name      0
substitute0      0
substitute1      0
substitute2      0
substitute3      0
substitute4      0
sideEffect0      0
sideEffect1      0
sideEffect2      0
sideEffect3      0
sideEffect4      0
sideEffect5      0
sideEffect6      0
sideEffect7      0
sideEffect8      0
sideEffect9      0
sideEffect10     0
sideEffect11     0
sideEffect12     0
sideEffect13     0
sideEffect14     0
```

sideEffect15	0
sideEffect16	0
sideEffect17	0
sideEffect18	0
sideEffect19	0
sideEffect20	0
sideEffect21	0
sideEffect22	0
sideEffect23	0
sideEffect24	0
sideEffect25	0
sideEffect26	0
sideEffect27	0
sideEffect28	0
sideEffect29	0
sideEffect30	0
sideEffect31	0
sideEffect32	0
sideEffect33	0
sideEffect34	0
sideEffect35	0
sideEffect36	0
sideEffect37	0
sideEffect38	0
sideEffect39	0
sideEffect40	0
sideEffect41	0
use0	0
use1	0
use2	0
use3	0
use4	0
Chemical Class	0
Habit Forming	0
Therapeutic Class	0
Action Class	0

dtype: int64

### 3.1 Creating Checkpoint 1

```
[358]: df_cleaned = df.copy()
```



## 4 EDA(Exploratory Data Analysis.)

### 4.0.1 Explore how many sideeffects each medicine has and identify medicines with the most substitutes.

```
[359]: #Create a list of side effect columns
side_effect_columns = [col for col in df_cleaned.columns if 'sideEffect' in col]

df_cleaned[side_effect_columns].head(3)
```

```
[359]:   sideEffect0 sideEffect1   sideEffect2   sideEffect3   sideEffect4 \
0   Vomiting      Nausea      Diarrhea      Unknown      Unknown
1   Vomiting      Nausea  Abdominal pain      Diarrhea      Unknown
2      Nausea   Vomiting      Diarrhea  Upset stomach  Stomach pain

      sideEffect5 sideEffect6 sideEffect7 sideEffect8 sideEffect9 ... \
0           Unknown      Unknown      Unknown      Unknown      Unknown ...
1           Unknown      Unknown      Unknown      Unknown      Unknown ...
2  Allergic reaction  Dizziness      Headache      Rash      Hives ...

      sideEffect32 sideEffect33 sideEffect34 sideEffect35 sideEffect36 \
0           Unknown      Unknown      Unknown      Unknown      Unknown
1           Unknown      Unknown      Unknown      Unknown      Unknown
2           Unknown      Unknown      Unknown      Unknown      Unknown

      sideEffect37 sideEffect38 sideEffect39 sideEffect40 sideEffect41
0           Unknown      Unknown      Unknown      Unknown      Unknown
1           Unknown      Unknown      Unknown      Unknown      Unknown
2           Unknown      Unknown      Unknown      Unknown      Unknown

[3 rows x 42 columns]
```

```
[360]: # Calculate the count of known side effects for each drug by counting entries_
↳that are not "Unknown"
df_cleaned['total_side_effect_recorded'] = df_cleaned[side_effect_columns].
↳apply(lambda x: (x != "Unknown").sum()), axis=1)
df_cleaned.head(3)
```

```
[360]:           name           substitute0 \
0  augmentin 625 duo tablet  Penciclav 500 mg/125 mg Tablet
1      azithral 500 tablet      Zithrocare 500mg Tablet
2      ascoril ls syrup      Solvin LS Syrup

      substitute1           substitute2           substitute3 \
0  Moxikind-CV 625 Tablet  Moxiforce-CV 625 Tablet  Fightox 625 Tablet
1      Azax 500 Tablet      Zady 500 Tablet  Cazithro 500mg Tablet
2  Ambrodil-LX Syrup      Zerotuss XP Syrup      Capex LS Syrup
```

	substitute4	sideEffect0	sideEffect1	sideEffect2	\
0	Novamox CV 625mg Tablet	Vomiting	Nausea	Diarrhea	
1	Trulimax 500mg Tablet	Vomiting	Nausea	Abdominal pain	
2	Broxum LS Syrup	Nausea	Vomiting	Diarrhea	

	sideEffect3	...	use0	use1	use2	\
0	Unknown	...	Treatment of Bacterial infections	Unknown	Unknown	
1	Diarrhea	...	Treatment of Bacterial infections	Unknown	Unknown	
2	Upset stomach	...	Treatment of Cough with mucus	Unknown	Unknown	

	use3	use4	Chemical Class	Habit Forming	Therapeutic Class	\
0	Unknown	Unknown	Unknown	No	ANTI INFECTIVES	
1	Unknown	Unknown	Macrolides	No	ANTI INFECTIVES	
2	Unknown	Unknown	Unknown	No	RESPIRATORY	

	Action Class	total_side_effect_recorded
0	Unknown	3
1	Macrolides	4
2	Unknown	14

[3 rows x 58 columns]

```
[361]: #Top 10 Medicine that has most Side effects
df_cleaned[['name', 'total_side_effect_recorded']].sort_values(by =
↳ 'total_side_effect_recorded', ascending=False).head(10)
```

```
[361]:
```

	name	total_side_effect_recorded
30664	balila capsule	42
30832	balila 25mg capsule	42
235196	waycef o 200mg/200mg tablet	35
235198	wincef-o tablet	35
37699	brefix o 200mg/200mg tablet	35
46980	ceftrue-o tablet	35
235822	winfex o 200mg/200mg tablet	35
142110	milixim-o tablet	35
169329	netfix-ox tablet	35
48126	cefistar-o tablet	35

#### 4.0.2 Explore how many substitutes each medicine has

```
[362]: #Create a list of substitute columns
substitute_columns = [col for col in df_cleaned.columns if 'substitute' in col]

df_cleaned[substitute_columns].head(3)
```

```
[362]:
```

	substitute0	substitute1	\
0	Penciclav 500 mg/125 mg Tablet	Moxikind-CV 625 Tablet	

1	Zithrocare 500mg Tablet	Azax 500 Tablet
2	Solvin LS Syrup	Ambrodil-LX Syrup

	substitute2	substitute3	substitute4
0	Moxiforce-CV 625 Tablet	Fightox 625 Tablet	Novamox CV 625mg Tablet
1	Zady 500 Tablet	Cazithro 500mg Tablet	Trulimax 500mg Tablet
2	Zerotuss XP Syrup	Capex LS Syrup	Broxum LS Syrup

```
[363]: df_cleaned["total_substitute_counts"]=df_cleaned[substitute_columns].
        ↪apply(lambda x: (x!= 'UnKnown').sum(),axis= 1)
df_cleaned.head(3)
```

```
[363]:
```

	name	substitute0 \
0	augmentin 625 duo tablet	Penciclav 500 mg/125 mg Tablet
1	azithral 500 tablet	Zithrocare 500mg Tablet
2	ascoril ls syrup	Solvin LS Syrup

	substitute1	substitute2	substitute3 \
0	Moxikind-CV 625 Tablet	Moxiforce-CV 625 Tablet	Fightox 625 Tablet
1	Azax 500 Tablet	Zady 500 Tablet	Cazithro 500mg Tablet
2	Ambrodil-LX Syrup	Zerotuss XP Syrup	Capex LS Syrup

	substitute4	sideEffect0	sideEffect1	sideEffect2 \
0	Novamox CV 625mg Tablet	Vomiting	Nausea	Diarrhea
1	Trulimax 500mg Tablet	Vomiting	Nausea	Abdominal pain
2	Broxum LS Syrup	Nausea	Vomiting	Diarrhea

	sideEffect3 ...	use1	use2	use3	use4	Chemical Class \
0	UnKnown ...	UnKnown	UnKnown	UnKnown	UnKnown	UnKnown
1	Diarrhea ...	UnKnown	UnKnown	UnKnown	UnKnown	Macrolides
2	Upset stomach ...	UnKnown	UnKnown	UnKnown	UnKnown	UnKnown

	Habit	Forming	Therapeutic Class	Action Class	total_side_effect_recorded \
0	No	ANTI	INFECTIVES	UnKnown	3
1	No	ANTI	INFECTIVES	Macrolides	4
2	No	RESPIRATORY	UnKnown		14

	total_substitute_counts
0	5
1	5
2	5

[3 rows x 59 columns]

### 4.0.3 Identify which substitute is used in the highest number of medicines.

```
[364]: # Count non-"Unknown" values for each substitute column
substitute_counts = pd.DataFrame(df_cleaned[substitute_columns].apply(lambda_
    ↪col: (col != "UnKnown")).sum(axis = 0),columns= ['Counts']).reset_index()
substitute_counts=substitute_counts.rename(columns={'index':'substitutes'})
substitute_counts
```

```
[364]:
```

	substitutes	Counts
0	substitute0	215194
1	substitute1	210818
2	substitute2	207440
3	substitute3	204322
4	substitute4	201657

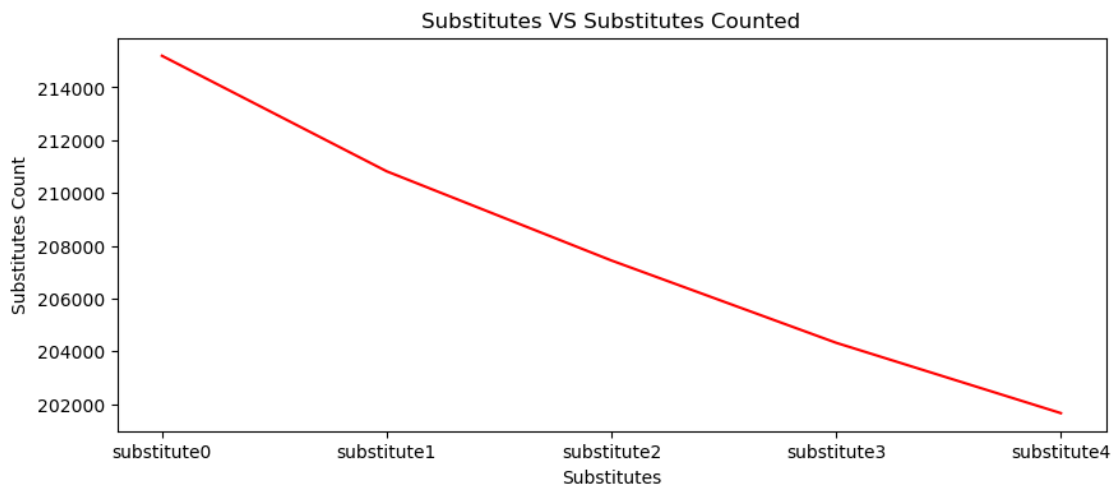
```
[365]: #creating a line with the missing value

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 4))
sns.lineplot(x='substitutes', y='Counts', data=substitute_counts, color='red')

plt.xlabel('Substitutes')
plt.ylabel('Substitutes Count')
plt.title("Substitutes VS Substitutes Counted")
plt.xticks(rotation=0)
plt.show()

# Show the plot
plt.show()
```



#### 4.0.4 Explore the total uses of the medicines

```
[366]: use_columns = [f'use{i}' for i in range(5)]
       use_columns
```

```
[366]: ['use0', 'use1', 'use2', 'use3', 'use4']
```

```
[367]: df_cleaned['total_uses'] = df_cleaned[use_columns].apply(lambda x: x != 'UnKnown').sum(axis=1)
       df_cleaned.sort_values(by='total_uses', ascending=False).head(3)
```

```
[367]:
```

	name	substitute0	substitute1	\
152854	mincetam 800mg tablet	Cgtam 800mg Tablet	Leepan 800 Tablet	
172310	navmit 4mg tablet	Predace 4 Tablet	Coelone 4mg Tablet	
235271	walbeta la 20mg tablet	Prograin 20mg Tablet	Nigrain 20mg Tablet	
	substitute2	substitute3	substitute4	\
152854	Geocetam 800mg Tablet	Piramax 800 Tablet	Sumocetam 800 Tablet	
172310	Melpred 4mg Tablet	Pilsone 4mg Tablet	Cortilog 4mg Tablet	
235271	Betagem 20mg Tablet	Signalol 20mg Tablet	Arminol 20mg Tablet	
	sideEffect0	sideEffect1	\	
152854	Weight gain	Nervousness		
172310	Thinning of skin	Increased risk of infection		
235271	Tiredness	Weakness		
	sideEffect2	sideEffect3	\	
152854	Abnormality of voluntary movements	UnKnown		
172310	Reduction in bone density	Weight gain		
235271	Raynaud's phenomenon	Arrhythmia (irregular heartbeats)		
	use2	use3	\	
152854	... Dementia in Parkinson's disease	Age related memory loss		
172310	... Treatment of Allergic conditions	Treatment of Eye disorders		
235271	... Prevention of migraine	Treatment of Anxiety		
	use4	Chemical Class	\	
152854	Head injury	Alpha Amino Acids Derivatives		
172310	Treatment of Skin disorders	Glucocorticoids		
235271	Treatment of Arrhythmia	Naphthalenes derivatives		
	Habit Forming Therapeutic Class	Action Class	\	
152854	No	NEURO CNS	Nootropic agent	
172310	No	HORMONES	Glucocorticoids	
235271	No	CARDIAC	Beta blocker- Non selective	

	total_side_effect_recorded	total_substitute_counts	total_uses
152854	3	5	5
172310	7	5	5
235271	7	5	5

[3 rows x 60 columns]

#### 4.0.5 Explore the most common uses of the medicines.

```
[368]: # Combine all use columns into one
use_columns = [f'use{i}' for i in range(5)]

uses = df_cleaned[use_columns].apply(lambda x: x.value_counts()).sum(axis = 1)
uses = pd.DataFrame(uses, columns = ['uses_counts']).reset_index()
uses = uses.rename(columns = {'index': 'uses'})

# Filter out rows where 'uses' is "Unknown" or null
uses = uses[uses.apply(lambda x: (x!= 'UnKnown'))]
uses = uses.dropna()

#sorting the dataframe
uses = uses.sort_values("uses_counts", ascending = False)

#Top 10 using
uses.head(10)
```

```
[368]:
```

	uses	uses_counts
549	Treatment of Bacterial infections	37129.0
313	Pain relief	21152.0
736	Treatment of Peptic ulcer disease	12581.0
627	Treatment of Gastroesophageal reflux disease (...)	12556.0
799	Treatment of Type 2 diabetes mellitus	10250.0
41	Bacterial infections	9719.0
649	Treatment of Hypertension (high blood pressure)	7178.0
525	Treatment of Allergic conditions	5766.0
786	Treatment of Sneezing and runny nose due to al...	4904.0
637	Treatment of Heartburn	4381.0

#### 4.0.6 Explore 50 most used chemical (Excluding 'Unknown')

```
[369]: df_cleaned['Chemical Class'][df_cleaned['Chemical Class'].apply(lambda x: x!=
↳ 'UnKnown')].value_counts().head(50)
```

```
[369]: Chemical Class
Fluoroquinolone 7007
Broad Spectrum (Third & fourth generation cephalosporins) 6407
```

Macrolides	4808
Sulfinylbenzimidazole Derivative	4395
Broad spectrum {Third & fourth generation cephalosporins}	3936
Glucocorticoids, progestogens and derivatives	2604
Azoles {Triazoles}	2443
Intermediate spectrum {Second generation cephalosporins}	2375
Carbazole Derivative	2278
Glucocorticoids	2238
Azole derivatives {Imidazoles}	2065
Benzodiazepines Derivative	2025
Aminoglycosides	1951
Piperazine Derivatives	1818
P-Aminophenol Derivative	1563
Aminopenicillins {Penicillins}	1528
Pyrrole & heptanoic acid derivative	1505
Anabolic steroid	1358
Timoprazole Derivative	1327
Phenylacetic acid Derivative	1304
Progesterone Derivative	1263
Sulfone and Pyridine Derivative	1094
Diphenylmethane Derivative	1035
Carbapenem derivative	1011
Cobalamin Derivative	1008
Dihydropyridinecarboxylic acids derivatives	966
Phenylpyrimidine derivatives	947
Histamine Analog	944
Benzimidazole derivative	922
Azoles derivatives	916
Diphenylethers Derivative	845
2-Benzimidazolylcarbamic acid esters	790
Phenylbutylamine Derivative	752
Bile Acids and Salts	751
Thienobenzodiazepine Derivative	746
Dichlorobenzenes Derivative	742
Alcohol & phenols	718
Piperazine Derivative	700
Sesquiterpene lactones	680
Biguanides Derivative	680
Phenylmethyl Piperazinyl Derivative	635
Valiolamine derivative	584
Pyrrolidinone & Acetamide Derivative	559
Dibenzocycloheptenes Derivative	556
Benzenesulfonamide Derivative	552
Thiazole Derivative	540
Narrow-spectrum {First generation cephalosporins}	539
Oxazolidinone derivative	529
Nucleoside analog	520

Narrow- spectrum {First generation cephalosporins} 518  
Name: count, dtype: int64

#### 4.0.7 Explore the uses of Therapeutic class (Excluding 'Unknown')

```
[370]: df_cleaned['Therapeutic Class'][df_cleaned['Therapeutic Class'].apply(lambda x:  
↳x!= 'UnKnown')].value_counts().sort_values(ascending = False)
```

```
[370]: Therapeutic Class  
ANTI INFECTIVES 50459  
GASTRO INTESTINAL 30442  
PAIN ANALGESICS 29187  
NEURO CNS 21524  
RESPIRATORY 21284  
CARDIAC 16774  
ANTI DIABETIC 10457  
OPHTHAL 9494  
DERMA 8949  
HORMONES 4927  
GYNAECOLOGICAL 4094  
VITAMINS MINERALS NUTRIENTS 3885  
ANTI NEOPLASTICS 3202  
BLOOD RELATED 2464  
UROLOGY 1720  
OPHTHAL OTOLOGICALS 1558  
ANTI MALARIALS 1466  
SEX STIMULANTS REJUVENATORS 682  
OTHERS 464  
OTOLOGICALS 451  
VACCINES 306  
STOMATOLOGICALS 162  
Name: count, dtype: int64
```

#### 4.0.8 Explore the uses of Action class (Excluding 'Unknown')

```
[371]: df_cleaned['Action Class'][df_cleaned['Action Class'].apply(lambda x:x!=  
↳'UnKnown')].value_counts().sort_values(ascending = False).head(50)
```

```
[371]: Action Class  
Cephalosporins: 3 generation 10901  
Quinolones/ Fluroquinolones 7011  
Fungal ergosterol synthesis inhibitor 5990  
Proton pump inhibitors 5734  
Macrolides 5109  
Glucocorticoids 4779  
H1 Antihistaminics (second Generation) 3702  
HMG CoA inhibitors (statins) 2561
```



Cephalosporins: 2nd generation	2448
Benzodiazepines	2447
NSAID's- Non-Selective COX 1&2 Inhibitors (acetic acid)	2426
Serotonin antagonists (5-HT3 antagonists)	2369
Atypical Antipsychotics	2364
Aminoglycosides	1951
Selective Serotonin Reuptake inhibitors (SSRIs)	1829
Angiotensin receptor blockers(ARB)	1747
Sodium channel modulators (AED)	1600
Analgesic & Antipyretic-PCM	1563
Cell wall active agent -Extended spectrum Penicillin	1536
Vitamins	1364
Anabolic steroid	1358
Natural Progesterone	1263
NSAID's -Selective COX-2 Inhibitors	1213
Beta blocker- Cardioslective	1206
Calcium channel blockers- Dihydropyridines (DHP)	1166
Cephalosporins: 1st generation	1057
Cell wall active agent -Carbapenems	1011
Antiprotozoal agents	966
Nootropic agent	944
Histamine analog- Meniere's Disease	944
Sulfonylureas (Insulin Secretagogues)	896
NSAID's-Non-Selective COX 1&2 Inhibitors (Others)	872
H1 Antihistaminics (First Generation)	844
Hepatoprotectives	837
Antimalarial- Artemisinin and derivatives	831
Tricyclic antidepressants	779
Synaptic vesicle 2 A protein ligand (AED)	685
Biguanides	680
Alpha-glucosidase inhibitors	679
Xanthine oxidase Inhibitors-gout	655
DPP-4 inhibitors	648
Theophylline & its derivatives	610
Ectoparasitocides	609
Progestins (First generation)	607
Serotonin-norepinephrine reuptake inhibitors (SNRIs)	582
Alpha 2 delta ligands (AED)	579
Proteolytic Enzymes	578
Angiotensin-converting enzyme (ACE) inhibitors	568
Phosphodiesterase-V inhibitors	564
Oxazolidinone	529
Name: count, dtype: int64	

## 5 Classification Analysis

### 5.0.1 Top 50 Chemical Classes by Frequency of Medicines (Excluding 'Unknown')

```
[372]: med_frequency_by_chemical_class = df_cleaned.groupby('Chemical Class')['name'].  
       ↪count().loc[lambda x: x.index != "Unknown"].sort_values(ascending=False)  
       med_frequency_by_chemical_class.head(50)
```

```
[372]: Chemical Class  
Fluoroquinolone 7007  
Broad Spectrum (Third & fourth generation cephalosporins) 6407  
Macrolides 4808  
Sulfinylbenzimidazole Derivative 4395  
Broad spectrum (Third & fourth generation cephalosporins} 3936  
Gluco/mineralocorticoids, progestogins and derivatives 2604  
Azoles {Triazoles} 2443  
Intermediate spectrum {Second generation cephalosporins} 2375  
Carbazole Derivative 2278  
Glucocorticoids 2238  
Azole derivatives {Imidazoles} 2065  
Benzodiazepines Derivative 2025  
Aminoglycosides 1951  
Piperazine Derivatives 1818  
P-Aminophenol Derivative 1563  
Aminopenicillins {Penicillins} 1528  
Pyrrole & heptanoic acid derivative 1505  
Anabolic steroid 1358  
Timoprazole Derivative 1327  
Phenylacetic acid Derivative 1304  
Progesterone Derivative 1263  
Sulfone and Pyridine Derivative 1094  
Diphenylmethane Derivative 1035  
Carbapenem derivative 1011  
Cobalamin Derivative 1008  
Dihydropyridinecarboxylic acids derivatives 966  
Phenylpyrimidine derivatives 947  
Histamine Analog 944  
Benzimidazole derivative 922  
Azoles derivatives 916  
Diphenylethers Derivative 845  
2-Benzimidazolylcarbamic acid esters 790  
Phenylbutylamine Derivative 752  
Bile Acids and Salts 751  
Thienobenzodiazepine Derivative 746  
Dichlorobenzenes Derivative 742  
Alcohol & phenols 718  
Piperazine Derivative 700
```

Biguanides Derivative	680
Sesquiterpene lactones	680
Phenylmethyl Piperazinyl Derivative	635
Valiolamine derivative	584
Pyrrolidinone & Acetamide Derivative	559
Dibenzocycloheptenes Derivative	556
Benzenesulfonamide Derivative	552
Thiazole Derivative	540
Narrow-spectrum {First generation cephalosporins}	539
Oxazolidinone derivative	529
Nucleoside analog	520
Narrow- specttrum {First generation cephalosporins}	518
Name: name, dtype: int64	

## 5.0.2 Top 50 Chemical Classes by Reported Side Effects Count (Excluding 'Unknown')

```
[373]: #loc[lambda x: x.index != "UnKnown"] excluding the index "unknow" from the
      ↪result

side_effect_frequency_by_chemical_class = df_cleaned.groupby(['Chemical_
      ↪Class'])[side_effect_columns].count().sum(axis = 1).loc[lambda x: x.index !=
      ↪'UnKnown'].sort_values(ascending = False)
side_effect_frequency_by_chemical_class.head(50)
```

```
[373]:
```

Chemical Class	
Fluoroquinolone	294294
Broad Spectrum (Third & fourth generation cephalosporins)	269094
Macrolides	201936
Sulfinylbenzimidazole Derivative	184590
Broad spectrum (Third & fourth generation cephalosporins)	165312
Glucocorticoids, progestogens and derivatives	109368
Azoles {Triazoles}	102606
Intermediate spectrum {Second generation cephalosporins}	99750
Carbazole Derivative	95676
Glucocorticoids	93996
Azole derivatives {Imidazoles}	86730
Benzodiazepines Derivative	85050
Aminoglycosides	81942
Piperazine Derivatives	76356
P-Aminophenol Derivative	65646
Aminopenicillins {Penicillins}	64176
Pyrrole & heptanoic acid derivative	63210
Anabolic steroid	57036
Timoprazole Derivative	55734
Phenylacetic acid Derivative	54768
Progesterone Derivative	53046

Sulfone and Pyridine Derivative	45948
Diphenylmethane Derivative	43470
Carbapenem derivative	42462
Cobalamin Derivative	42336
Dihydropyridinecarboxylic acids derivatives	40572
Phenylpyrimidine derivatives	39774
Histamine Analog	39648
Benzimidazole derivative	38724
Azoles derivatives	38472
Diphenylethers Derivative	35490
2-Benzimidazolylcarbamic acid esters	33180
Phenylbutylamine Derivative	31584
Bile Acids and Salts	31542
Thienobenzodiazepine Derivative	31332
Dichlorobenzenes Derivative	31164
Alcohol & phenols	30156
Piperazine Derivative	29400
Biguanides Derivative	28560
Sesquiterpene lactones	28560
Phenylmethyl Piperaziny Derivative	26670
Valiolamine derivative	24528
Pyrrolidinone & Acetamide Derivative	23478
Dibenzocycloheptenes Derivative	23352
Benzenesulfonamide Derivative	23184
Thiazole Derivative	22680
Narrow-spectrum {First generation cephalosporins}	22638
Oxazolidinone derivative	22218
Nucleoside analog	21840
Narrow- specttrum {First generation cephalosporins}	21756
dtype: int64	

### 5.0.3 Top 50 Chemical Classes by Usage Count Across All Use Columns (Excluding 'Unknown')

```
[374]: total_usage_frequency_by_chemical_class = df_cleaned.groupby(['Chemical_
↳Class'])[use_columns].count().sum(axis = 1).loc[lambda x: x.index !=_
↳'UnKnown'].sort_values(ascending = False)
total_usage_frequency_by_chemical_class.head(50)
```

Chemical Class	
Fluoroquinolone	35035
Broad Spectrum (Third & fourth generation cephalosporins)	32035
Macrolides	24040
Sulfinylbenzimidazole Derivative	21975
Broad spectrum (Third & fourth generation cephalosporins}	19680
Glucocorticoids, progestogens and derivatives	13020
Azoles {Triazoles}	12215

Intermediate spectrum {Second generation cephalosporins}	11875
Carbazole Derivative	11390
Glucocorticoids	11190
Azole derivatives {Imidazoles}	10325
Benzodiazepines Derivative	10125
Aminoglycosides	9755
Piperazine Derivatives	9090
P-Aminophenol Derivative	7815
Aminopenicillins {Penicillins}	7640
Pyrrole & heptanoic acid derivative	7525
Anabolic steroid	6790
Timoprazole Derivative	6635
Phenylacetic acid Derivative	6520
Progesterone Derivative	6315
Sulfone and Pyridine Derivative	5470
Diphenylmethane Derivative	5175
Carbapenem derivative	5055
Cobalamin Derivative	5040
Dihydropyridinecarboxylic acids derivatives	4830
Phenylpyrimidine derivatives	4735
Histamine Analog	4720
Benzimidazole derivative	4610
Azoles derivatives	4580
Diphenylethers Derivative	4225
2-Benzimidazolylcarbamic acid esters	3950
Phenylbutylamine Derivative	3760
Bile Acids and Salts	3755
Thienobenzodiazepine Derivative	3730
Dichlorobenzenes Derivative	3710
Alcohol & phenols	3590
Piperazine Derivative	3500
Biguanides Derivative	3400
Sesquiterpene lactones	3400
Phenylmethyl Piperazinyl Derivative	3175
Valiolamine derivative	2920
Pyrrolidinone & Acetamide Derivative	2795
Dibenzocycloheptenes Derivative	2780
Benzenesulfonamide Derivative	2760
Thiazole Derivative	2700
Narrow-spectrum {First generation cephalosporins}	2695
Oxazolidinone derivative	2645
Nucleoside analog	2600
Narrow- specttrum {First generation cephalosporins}	2590
dtype: int64	

#### 5.0.4 Chemical Data Summary: Usage, Side Effects, and Total Frequency

```
[375]: all_abt_chemicals = pd.DataFrame({'Med_frequency':  
    ↳med_frequency_by_chemical_class, 'Side_effect_frequency':  
    ↳side_effect_frequency_by_chemical_class, 'Total_usage_frequency':  
    ↳total_usage_frequency_by_chemical_class})  
all_abt_chemicals.head(50)
```

```
[375]:
```

Chemical Class	Med_frequency \
Fluoroquinolone	7007
Broad Spectrum (Third & fourth generation cepha...	6407
Macrolides	4808
Sulfinylbenzimidazole Derivative	4395
Broad spectrum (Third & fourth generation cepha...	3936
Gluco/mineralocorticoids, progestogins and deri...	2604
Azoles {Triazoles}	2443
Intermediate spectrum {Second generation cephal...	2375
Carbazole Derivative	2278
Glucocorticoids	2238
Azole derivatives {Imidazoles}	2065
Benzodiazepines Derivative	2025
Aminoglycosides	1951
Piperazine Derivatives	1818
P-Aminophenol Derivative	1563
Aminopenicillins {Penicillins}	1528
Pyrrole & heptanoic acid derivative	1505
Anabolic steroid	1358
Timoprazole Derivative	1327
Phenylacetic acid Derivative	1304
Progesterone Derivative	1263
Sulfone and Pyridine Derivative	1094
Diphenylmethane Derivative	1035
Carbapenem derivative	1011
Cobalamin Derivative	1008
Dihydropyridinecarboxylic acids derivatives	966
Phenylpyrimidine derivatives	947
Histamine Analog	944
Benzimidazole derivative	922
Azoles derivatives	916
Diphenylethers Derivative	845
2-Benzimidazolylcarbamic acid esters	790
Phenylbutylamine Derivative	752
Bile Acids and Salts	751
Thienobenzodiazepine Derivative	746
Dichlorobenzenes Derivative	742
Alcohol & phenols	718

Piperazine Derivative	700
Biguanides Derivative	680
Sesquiterpene lactones	680
Phenylmethyl Piperazinyll Derivative	635
Valiolamine derivative	584
Pyrrolidinone & Acetamide Derivative	559
Dibenzocycloheptenes Derivative	556
Benzenesulfonamide Derivative	552
Thiazole Derivative	540
Narrow-spectrum {First generation cephalosporins}	539
Oxazolidinone derivative	529
Nucleoside analog	520
Narrow- specttrum {First generation cephalospor...	518

Side\_effect\_frequency \

Chemical Class	
Fluoroquinolone	294294
Broad Spectrum (Third & fourth generation cepha...	269094
Macrolides	201936
Sulfinylbenzimidazole Derivative	184590
Broad spectrum (Third & fourth generation cepha...	165312
Glucoc/mineralocorticoids, progestogins and deri...	109368
Azoles {Triazoles}	102606
Intermediate spectrum {Second generation cephal...	99750
Carbazole Derivative	95676
Glucocorticoids	93996
Azole derivatives {Imidazoles}	86730
Benzodiazepines Derivative	85050
Aminoglycosides	81942
Piperazine Derivatives	76356
P-Aminophenol Derivative	65646
Aminopenicillins {Penicillins}	64176
Pyrrole & heptanoic acid derivative	63210
Anabolic steroid	57036
Timoprazole Derivative	55734
Phenylacetic acid Derivative	54768
Progesterone Derivative	53046
Sulfone and Pyridine Derivative	45948
Diphenylmethane Derivative	43470
Carbapenem derivative	42462
Cobalamin Derivative	42336
Dihydropyridinecarboxylic acids derivatives	40572
Phenylpyrimidine derivatives	39774
Histamine Analog	39648
Benzimidazole derivative	38724
Azoles derivatives	38472
Diphenylethers Derivative	35490

2-Benzimidazolylcarbamic acid esters	33180
Phenylbutylamine Derivative	31584
Bile Acids and Salts	31542
Thienobenzodiazepine Derivative	31332
Dichlorobenzenes Derivative	31164
Alcohol & phenols	30156
Piperazine Derivative	29400
Biguanides Derivative	28560
Sesquiterpene lactones	28560
Phenylmethyl Piperazinyl Derivative	26670
Valiolamine derivative	24528
Pyrrolidinone & Acetamide Derivative	23478
Dibenzocycloheptenes Derivative	23352
Benzenesulfonamide Derivative	23184
Thiazole Derivative	22680
Narrow-spectrum {First generation cephalosporins}	22638
Oxazolidinone derivative	22218
Nucleoside analog	21840
Narrow- specttrum {First generation cephalospor...	21756

#### Total\_usage\_frequency

Chemical Class	
Fluoroquinolone	35035
Broad Spectrum (Third & fourth generation cepha...	32035
Macrolides	24040
Sulfinylbenzimidazole Derivative	21975
Broad spectrum (Third & fourth generation cepha...	19680
Gluco/mineralocorticoids, progestogins and deri...	13020
Azoles {Triazoles}	12215
Intermediate spectrum {Second generation cephal...	11875
Carbazole Derivative	11390
Glucocorticoids	11190
Azole derivatives {Imidazoles}	10325
Benzodiazepines Derivative	10125
Aminoglycosides	9755
Piperazine Derivatives	9090
P-Aminophenol Derivative	7815
Aminopenicillins {Penicillins}	7640
Pyrrole & heptanoic acid derivative	7525
Anabolic steroid	6790
Timoprazole Derivative	6635
Phenylacetic acid Derivative	6520
Progesterone Derivative	6315
Sulfone and Pyridine Derivative	5470
Diphenylmethane Derivative	5175
Carbapenem derivative	5055
Cobalamin Derivative	5040



Dihydropyridinecarboxylic acids derivatives	4830
Phenylpyrimidine derivatives	4735
Histamine Analog	4720
Benzimidazole derivative	4610
Azoles derivatives	4580
Diphenylethers Derivative	4225
2-Benzimidazolylcarbamic acid esters	3950
Phenylbutylamine Derivative	3760
Bile Acids and Salts	3755
Thienobenzodiazepine Derivative	3730
Dichlorobenzenes Derivative	3710
Alcohol & phenols	3590
Piperazine Derivative	3500
Biguanides Derivative	3400
Sesquiterpene lactones	3400
Phenylmethyl Piperaziny Derivative	3175
Valiolamine derivative	2920
Pyrrolidinone & Acetamide Derivative	2795
Dibenzocycloheptenes Derivative	2780
Benzenesulfonamide Derivative	2760
Thiazole Derivative	2700
Narrow-spectrum {First generation cephalosporins}	2695
Oxazolidinone derivative	2645
Nucleoside analog	2600
Narrow- specttrum {First generation cephalospor...	2590

### 5.0.5 Top 50 Action Classes by Frequency of Medicines (Excluding 'Unknown')

```
[376]: med_frequency_by_action_class = df_cleaned.groupby(['Action Class'])['name'].
        ↪count().loc[lambda x: x.index != "Unknown"].sort_values(ascending = False)
med_frequency_by_action_class.head(50)
```

[376]: Action Class	
Cephalosporins: 3 generation	10901
Quinolones/ Fluroquinolones	7011
Fungal ergosterol synthesis inhibitor	5990
Proton pump inhibitors	5734
Macrolides	5109
Glucocorticoids	4779
H1 Antihistaminics (second Generation)	3702
HMG CoA inhibitors (statins)	2561
Cephalosporins: 2nd generation	2448
Benzodiazepines	2447
NSAID's- Non-Selective COX 1&2 Inhibitors (acetic acid)	2426
Serotonin antagonists (5-HT3 antagonists)	2369
Atypical Antipsychotics	2364
Aminoglycosides	1951

Selective Serotonin Reuptake inhibitors (SSRIs)	1829
Angiotensin receptor blockers (ARB)	1747
Sodium channel modulators (AED)	1600
Analgesic & Antipyretic-PCM	1563
Cell wall active agent -Extended spectrum Penicillin	1536
Vitamins	1364
Anabolic steroid	1358
Natural Progesterone	1263
NSAID's -Selective COX-2 Inhibitors	1213
Beta blocker- Cardioselective	1206
Calcium channel blockers- Dihydropyridines (DHP)	1166
Cephalosporins: 1st generation	1057
Cell wall active agent -Carbapenems	1011
Antiprotozoal agents	966
Histamine analog- Meniere's Disease	944
Nootropic agent	944
Sulfonylureas (Insulin Secretagogues)	896
NSAID's-Non-Selective COX 1&2 Inhibitors (Others)	872
H1 Antihistaminics (First Generation)	844
Hepatoprotectives	837
Antimalarial- Artemisinin and derivatives	831
Tricyclic antidepressants	779
Synaptic vesicle 2 A protein ligand (AED)	685
Biguanides	680
Alpha-glucosidase inhibitors	679
Xanthine oxidase Inhibitors-gout	655
DPP-4 inhibitors	648
Theophylline & its derivatives	610
Ectoparasiticides	609
Progestins (First generation)	607
Serotonin-norepinephrine reuptake inhibitors (SNRIs)	582
Alpha 2 delta ligands (AED)	579
Proteolytic Enzymes	578
Angiotensin-converting enzyme (ACE) inhibitors	568
Phosphodiesterase-V inhibitors	564
Oxazolidinone	529
Name: name, dtype: int64	

### 5.0.6 Top 50 Action Classes by Reported Side Effects Count (Excluding 'Unknown')¶

```
[377]: side_effect_frequency_by_action_class = df_cleaned.groupby(['Action_
↳ Class'])[side_effect_columns].count().sum(axis= 1).loc[lamba x: x.index !=
↳ "UnKnown"].sort_values(ascending = False)
side_effect_frequency_by_action_class.head(50)
```

```
[377]: Action Class
Cephalosporins: 3 generation 457842
```

Quinolones/ Fluroquinolones	294462
Fungal ergosterol synthesis inhibitor	251580
Proton pump inhibitors	240828
Macrolides	214578
Glucocorticoids	200718
H1 Antihistaminics (second Generation)	155484
HMG CoA inhibitors (statins)	107562
Cephalosporins: 2nd generation	102816
Benzodiazepines	102774
NSAID's- Non-Selective COX 1&2 Inhibitors (acetic acid)	101892
Serotonin antagonists (5-HT3 antagonists)	99498
Atypical Antipsychotics	99288
Aminoglycosides	81942
Selective Serotonin Reuptake inhibitors (SSRIs)	76818
Angiotensin receptor blockers(ARB)	73374
Sodium channel modulators (AED)	67200
Analgesic & Antipyretic-PCM	65646
Cell wall active agent -Extended spectrum Penicillin	64512
Vitamins	57288
Anabolic steroid	57036
Natural Progesterone	53046
NSAID's -Selective COX-2 Inhibitors	50946
Beta blocker- Cardioselective	50652
Calcium channel blockers- Dihydropyridines (DHP)	48972
Cephalosporins: 1st generation	44394
Cell wall active agent -Carbapenems	42462
Antiprotozoal agents	40572
Histamine analog- Meniere's Disease	39648
Nootropic agent	39648
Sulfonylureas (Insulin Secretagogues)	37632
NSAID's-Non-Selective COX 1&2 Inhibitors (Others)	36624
H1 Antihistaminics (First Generation)	35448
Hepatoprotectives	35154
Antimalarial- Artemisinin and derivatives	34902
Tricyclic antidepressants	32718
Synaptic vesicle 2 A protein ligand (AED)	28770
Biguanides	28560
Alpha-glucosidase inhibitors	28518
Xanthine oxidase Inhibitors-gout	27510
DPP-4 inhibitors	27216
Theophylline & its derivatives	25620
Ectoparasiticides	25578
Progestins (First generation)	25494
Serotonin-norepinephrine reuptake inhibitors (SNRIs)	24444
Alpha 2 delta ligands (AED)	24318
Proteolytic Enzymes	24276
Angiotensin-converting enzyme (ACE) inhibitors	23856

Phosphodiesterase-V inhibitors	23688
Oxazolidinone	22218
dtype: int64	

### 5.0.7 Top 50 Action Classes by Usage Count Across All Use Columns (Excluding 'Unknown')

```
[378]: total_usage_frequency_by_action_class = df_cleaned.groupby(['Action_
↳Class'])[use_columns].count().sum(axis =1).loc[lambda x: x.index !=
↳'Unknown'].sort_values(ascending = False)
total_usage_frequency_by_action_class.head(50)
```

```
[378]: Action Class
Cephalosporins: 3 generation                    54505
Quinolones/ Fluroquinolones                    35055
Fungal ergosterol synthesis inhibitor            29950
Proton pump inhibitors                           28670
Macrolides                                       25545
Glucocorticoids                                 23895
H1 Antihistaminics (second Generation)          18510
HMG CoA inhibitors (statins)                    12805
Cephalosporins: 2nd generation                  12240
Benzodiazepines                                 12235
NSAID's- Non-Selective COX 1&2 Inhibitors (acetic acid) 12130
Serotonin antagonists (5-HT3 antagonists)       11845
Atypical Antipsychotics                         11820
Aminoglycosides                                 9755
Selective Serotonin Reuptake inhibitors (SSRIs)  9145
Angiotensin receptor blockers(ARB)              8735
Sodium channel modulators (AED)                 8000
Analgesic & Antipyretic-PCM                     7815
Cell wall active agent -Extended spectrum Penicillin 7680
Vitamins                                         6820
Anabolic steroid                               6790
Natural Progesterone                           6315
NSAID's -Selective COX-2 Inhibitors             6065
Beta blocker- Cardiosselective                  6030
Calcium channel blockers- Dihydropyridines (DHP) 5830
Cephalosporins: 1st generation                  5285
Cell wall active agent -Carbapenems             5055
Antiprotozoal agents                           4830
Histamine analog- Meniere's Disease             4720
Nootropic agent                                4720
Sulfonylureas (Insulin Secretogogues)          4480
NSAID's-Non-Selective COX 1&2 Inhibitors (Others) 4360
H1 Antihistaminics (First Generation)          4220
Hepatoprotectives                              4185
```

Antimalarial- Artemisinin and derivatives	4155
Tricyclic antidepressants	3895
Synaptic vesicle 2 A protein ligand (AED)	3425
Biguanides	3400
Alpha-glucosidase inhibitors	3395
Xanthine oxidase Inhibitors-gout	3275
DPP-4 inhibitors	3240
Theophylline & its derivatives	3050
Ectoparasitocides	3045
Progestins (First generation)	3035
Serotonin-norepinephrine reuptake inhibitors (SNRIs)	2910
Alpha 2 delta ligands (AED)	2895
Proteolytic Enzymes	2890
Angiotensin-converting enzyme (ACE) inhibitors	2840
Phosphodiesterase-V inhibitors	2820
Oxazolidinone	2645
dtype: int64	

#### 5.0.8 Action Data Summary: Usage, Side Effects, and Total Frequency

```
[379]: all_abt_action = pd.DataFrame({'Med_frequency': med_frequency_by_action_class,
↳ 'Side_effect_frequency': side_effect_frequency_by_action_class,
↳ 'Total_usage_frequency': total_usage_frequency_by_action_class})
all_abt_action.head(50)
```

```
[379]:
```

Action Class	Med_frequency \
Cephalosporins: 3 generation	10901
Quinolones/ Fluroquinolones	7011
Fungal ergosterol synthesis inhibitor	5990
Proton pump inhibitors	5734
Macrolides	5109
Glucocorticoids	4779
H1 Antihistaminics (second Generation)	3702
HMG CoA inhibitors (statins)	2561
Cephalosporins: 2nd generation	2448
Benzodiazepines	2447
NSAID's- Non-Selective COX 1&2 Inhibitors (acet...	2426
Serotonin antagonists (5-HT3 antagonists)	2369
Atypical Antipsychotics	2364
Aminoglycosides	1951
Selective Serotonin Reuptake inhibitors (SSRIs)	1829
Angiotensin receptor blockers(ARB)	1747
Sodium channel modulators (AED)	1600
Analgesic & Antipyretic-PCM	1563
Cell wall active agent -Extended spectrum Penic...	1536
Vitamins	1364

Anabolic steroid	1358
Natural Progesterone	1263
NSAID's -Selective COX-2 Inhibitors	1213
Beta blocker- Cardiosselective	1206
Calcium channel blockers- Dihydropyridines (DHP)	1166
Cephalosporins: 1st generation	1057
Cell wall active agent -Carbapenems	1011
Antiprotozoal agents	966
Histamine analog- Meniere's Disease	944
Nootropic agent	944
Sulfonylureas (Insulin Secretogogues)	896
NSAID's-Non-Selective COX 1&2 Inhibitors (Others)	872
H1 Antihistaminics (First Generation)	844
Hepatoprotectives	837
Antimalarial- Artemisinin and derivatives	831
Tricyclic antidepressants	779
Synaptic vesicle 2 A protein ligand (AED)	685
Biguanides	680
Alpha-glucosidase inhibitors	679
Xanthine oxidase Inhibitors-gout	655
DPP-4 inhibitors	648
Theophylline & its derivatives	610
Ectoparasitocides	609
Progestins (First generation)	607
Serotonin-norepinephrine reuptake inhibitors (S...	582
Alpha 2 delta ligands (AED)	579
Proteolytic Enzymes	578
Angiotensin-converting enzyme (ACE) inhibitors	568
Phosphodiesterase-V inhibitors	564
Oxazolidinone	529

Side\_effect\_frequency \

Action Class	
Cephalosporins: 3 generation	457842
Quinolones/ Fluroquinolones	294462
Fungal ergosterol synthesis inhibitor	251580
Proton pump inhibitors	240828
Macrolides	214578
Glucocorticoids	200718
H1 Antihistaminics (second Generation)	155484
HMG CoA inhibitors (statins)	107562
Cephalosporins: 2nd generation	102816
Benzodiazepines	102774
NSAID's- Non-Selective COX 1&2 Inhibitors (acet...	101892
Serotonin antagonists (5-HT3 antagonists)	99498
Atypical Antipsychotics	99288
Aminoglycosides	81942

Selective Serotonin Reuptake inhibitors (SSRIs)	76818
Angiotensin receptor blockers(ARB)	73374
Sodium channel modulators (AED)	67200
Analgesic & Antipyretic-PCM	65646
Cell wall active agent -Extended spectrum Penic...	64512
Vitamins	57288
Anabolic steroid	57036
Natural Progesterone	53046
NSAID's -Selective COX-2 Inhibitors	50946
Beta blocker- Cardioselective	50652
Calcium channel blockers- Dihydropyridines (DHP)	48972
Cephalosporins: 1st generation	44394
Cell wall active agent -Carbapenems	42462
Antiprotozoal agents	40572
Histamine analog- Meniere's Disease	39648
Nootropic agent	39648
Sulfonylureas (Insulin Secretagogues)	37632
NSAID's-Non-Selective COX 1&2 Inhibitors (Others)	36624
H1 Antihistaminics (First Generation)	35448
Hepatoprotectives	35154
Antimalarial- Artemisinin and derivatives	34902
Tricyclic antidepressants	32718
Synaptic vesicle 2 A protein ligand (AED)	28770
Biguanides	28560
Alpha-glucosidase inhibitors	28518
Xanthine oxidase Inhibitors-gout	27510
DPP-4 inhibitors	27216
Theophylline & its derivatives	25620
Ectoparasiticides	25578
Progestins (First generation)	25494
Serotonin-norepinephrine reuptake inhibitors (S...	24444
Alpha 2 delta ligands (AED)	24318
Proteolytic Enzymes	24276
Angiotensin-converting enzyme (ACE) inhibitors	23856
Phosphodiesterase-V inhibitors	23688
Oxazolidinone	22218

#### Total\_usage\_frequency

Action Class	
Cephalosporins: 3 generation	54505
Quinolones/ Fluroquinolones	35055
Fungal ergosterol synthesis inhibitor	29950
Proton pump inhibitors	28670
Macrolides	25545
Glucocorticoids	23895
H1 Antihistaminics (second Generation)	18510
HMG CoA inhibitors (statins)	12805

Cephalosporins: 2nd generation	12240
Benzodiazepines	12235
NSAID's- Non-Selective COX 1&2 Inhibitors (acet...	12130
Serotonin antagonists (5-HT3 antagonists)	11845
Atypical Antipsychotics	11820
Aminoglycosides	9755
Selective Serotonin Reuptake inhibitors (SSRIs)	9145
Angiotensin receptor blockers(ARB)	8735
Sodium channel modulators (AED)	8000
Analgesic & Antipyretic-PCM	7815
Cell wall active agent -Extended spectrum Penic...	7680
Vitamins	6820
Anabolic steroid	6790
Natural Progesterone	6315
NSAID's -Selective COX-2 Inhibitors	6065
Beta blocker- Cardiosselective	6030
Calcium channel blockers- Dihydropyridines (DHP)	5830
Cephalosporins: 1st generation	5285
Cell wall active agent -Carbapenems	5055
Antiprotozoal agents	4830
Histamine analog- Meniere's Disease	4720
Nootropic agent	4720
Sulfonylureas (Insulin Secretagogues)	4480
NSAID's-Non-Selective COX 1&2 Inhibitors (Others)	4360
H1 Antihistaminics (First Generation)	4220
Hepatoprotectives	4185
Antimalarial- Artemisinin and derivatives	4155
Tricyclic antidepressants	3895
Synaptic vesicle 2 A protein ligand (AED)	3425
Biguanides	3400
Alpha-glucosidase inhibitors	3395
Xanthine oxidase Inhibitors-gout	3275
DPP-4 inhibitors	3240
Theophylline & its derivatives	3050
Ectoparasitocides	3045
Progestins (First generation)	3035
Serotonin-norepinephrine reuptake inhibitors (S...	2910
Alpha 2 delta ligands (AED)	2895
Proteolytic Enzymes	2890
Angiotensin-converting enzyme (ACE) inhibitors	2840
Phosphodiesterase-V inhibitors	2820
Oxazolidinone	2645



### 5.0.9 Top 50 Therapeutic Classes by Frequency of Medicines (Excluding ‘Unknown’)

```
[380]: med_frequency_by_Therapeutic_class = df_cleaned.groupby(['Therapeutic_
↳Class'])['name'].count().loc[lambda x: x.index != 'UnKnown'].
↳sort_values(ascending = False)
med_frequency_by_Therapeutic_class.head(50)
```

```
[380]: Therapeutic Class
ANTI INFECTIVES          50459
GASTRO INTESTINAL        30442
PAIN ANALGESICS          29187
NEURO CNS                21524
RESPIRATORY              21284
CARDIAC                  16774
ANTI DIABETIC            10457
OPHTHAL                  9494
DERMA                    8949
HORMONES                 4927
GYNAECOLOGICAL           4094
VITAMINS MINERALS NUTRIENTS 3885
ANTI NEOPLASTICS         3202
BLOOD RELATED            2464
UROLOGY                  1720
OPHTHAL OTOLOGICALS      1558
ANTI MALARIALS           1466
SEX STIMULANTS REJUVENATORS 682
OTHERS                   464
OTOLOGICALS              451
VACCINES                 306
STOMATOLOGICALS          162
Name: name, dtype: int64
```

### 5.0.10 Top 50 Therapeutic Classes by Reported Side Effects Count (Excluding ‘Unknown’)

```
[381]: side_effect_frequency_by_Therapeutic_class = df_cleaned.groupby(['Therapeutic_
↳Class'])[side_effect_columns].count().sum(axis =1).loc[lambda x: x.index !=
↳"UnKnown"].sort_values(ascending = False)
side_effect_frequency_by_Therapeutic_class.head(50)
```

```
[381]: Therapeutic Class
ANTI INFECTIVES          2119278
GASTRO INTESTINAL        1278564
PAIN ANALGESICS          1225854
NEURO CNS                904008
RESPIRATORY              893928
CARDIAC                  704508
```

ANTI DIABETIC	439194
OPHTHAL	398748
DERMA	375858
HORMONES	206934
GYNAECOLOGICAL	171948
VITAMINS MINERALS NUTRIENTS	163170
ANTI NEOPLASTICS	134484
BLOOD RELATED	103488
UROLOGY	72240
OPHTHAL OTOLOGICALS	65436
ANTI MALARIALS	61572
SEX STIMULANTS REJUVENATORS	28644
OTHERS	19488
OTOLOGICALS	18942
VACCINES	12852
STOMATOLOGICALS	6804

dtype: int64

#### 5.0.11 Top 50 Therapeutic Classes by Usage Count Across All Use Columns (Excluding 'Unknown')

```
[382]: total_usage_frequency_by_Therapeutic_class = df_cleaned.groupby(['Therapeutic_
↳Class'])[use_columns].count().sum(axis=1).loc[lambda x:x.index !=
↳"UnKnown"].sort_values(ascending = False)
total_usage_frequency_by_Therapeutic_class.head(50)
```

```
[382]: Therapeutic Class
ANTI INFECTIVES                252295
GASTRO INTESTINAL              152210
PAIN ANALGESICS                145935
NEURO CNS                      107620
RESPIRATORY                    106420
CARDIAC                        83870
ANTI DIABETIC                  52285
OPHTHAL                        47470
DERMA                          44745
HORMONES                       24635
GYNAECOLOGICAL                 20470
VITAMINS MINERALS NUTRIENTS    19425
ANTI NEOPLASTICS               16010
BLOOD RELATED                  12320
UROLOGY                        8600
OPHTHAL OTOLOGICALS           7790
ANTI MALARIALS                 7330
SEX STIMULANTS REJUVENATORS    3410
OTHERS                         2320
OTOLOGICALS                    2255
```

```
VACCINES                                1530
STOMATOLOGICALS                        810
dtype: int64
```

```
[383]: all_abt_Therapeutic_class = pd.DataFrame({'Med_frequency':  
    ↳ med_frequency_by_Therapeutic_class, 'Side_effect_frequency':  
    ↳ side_effect_frequency_by_Therapeutic_class, 'Total_usage_frequency':  
    ↳ total_usage_frequency_by_Therapeutic_class})  
all_abt_Therapeutic_class.head(50)
```

```
[383]:
```

Therapeutic Class	Med_frequency	Side_effect_frequency \
ANTI INFECTIVES	50459	2119278
GASTRO INTESTINAL	30442	1278564
PAIN ANALGESICS	29187	1225854
NEURO CNS	21524	904008
RESPIRATORY	21284	893928
CARDIAC	16774	704508
ANTI DIABETIC	10457	439194
OPHTHAL	9494	398748
DERMA	8949	375858
HORMONES	4927	206934
GYNAECOLOGICAL	4094	171948
VITAMINS MINERALS NUTRIENTS	3885	163170
ANTI NEOPLASTICS	3202	134484
BLOOD RELATED	2464	103488
UROLOGY	1720	72240
OPHTHAL OTOLOGICALS	1558	65436
ANTI MALARIALS	1466	61572
SEX STIMULANTS REJUVENATORS	682	28644
OTHERS	464	19488
OTOLOGICALS	451	18942
VACCINES	306	12852
STOMATOLOGICALS	162	6804

```
Total_usage_frequency
```

Therapeutic Class	Total_usage_frequency
ANTI INFECTIVES	252295
GASTRO INTESTINAL	152210
PAIN ANALGESICS	145935
NEURO CNS	107620
RESPIRATORY	106420
CARDIAC	83870
ANTI DIABETIC	52285
OPHTHAL	47470
DERMA	44745
HORMONES	24635

GYNAECOLOGICAL	20470
VITAMINS MINERALS NUTRIENTS	19425
ANTI NEOPLASTICS	16010
BLOOD RELATED	12320
UROLOGY	8600
OPHTHAL OTOLOGICALS	7790
ANTI MALARIALS	7330
SEX STIMULANTS REJUVENATORS	3410
OTHERS	2320
OTOLOGICALS	2255
VACCINES	1530
STOMATOLOGICALS	810

### 5.0.12 Creating Separate DataFrames for Drugs Based on Substitute Count

```
df_cleaned[df_cleaned[substitute_columns].apply(lambda x: x !=
'UnKnown').sum(axis=1)==5][['name','total_substitute_counts']]
df_cleaned[df_cleaned[substitute_columns].apply(lambda x: x !=
'UnKnown').sum(axis=1)==4][['name','total_substitute_counts']]
df_cleaned[df_cleaned[substitute_columns].apply(lambda x: x !=
'UnKnown').sum(axis=1)==3][['name','total_substitute_counts']]
df_cleaned[df_cleaned[substitute_columns].apply(lambda x: x !=
'UnKnown').sum(axis=1)==2][['name','total_substitute_counts']]
df_cleaned[df_cleaned[substitute_columns].apply(lambda x: x !=
'UnKnown').sum(axis=1)==1][['name','total_substitute_counts']]
df_cleaned[df_cleaned[substitute_columns].apply(lambda x: x != 'UnKnown').sum(axis
=1)==0][['name','total_substitute_counts']]
```

```
[384]: for i in range( 6):
        globals()[f"substitute_{i}"] = df_cleaned[df_cleaned[substitute_columns].
        ↪apply(lambda x: x != 'UnKnown').sum(axis=1) == i][['name',
        ↪'total_substitute_counts']]
```

```
[385]: #name of the medicine that has only 0 substitute
substitute_0.head(5)
```

```
[385]:
```

	name	total_substitute_counts
14	ambrodil-s syrup	0
72	aquasol a capsule	0
86	aerocort inhaler	0
93	atarax drops	0
95	antid 300mcg/ml injection	0

```
[386]: #name of the medicine that has only 1 substitute
substitute_1.head(5)
```

```
[386]:
```

	name	total_substitute_counts
4	avil 25 tablet	1

35	alkasol oral solution	1
108	alkasol oral solution sugar free	1
124	avanair 100 tablet	1
141	ambrolite-s expectorant	1

```
[387]: #name of the medicine that has only 2 substitute
substitute_2.head(5)
```

```
[387]:
```

	name	total_substitute_counts
53	alex cough lozenges lemon ginger	2
116	alerid-d tablet	2
147	adrenaline tartrate injection	2
161	addnok 0.2mg tablet	2
234	asthalin respirator solution	2

```
[388]: #name of the medicine that has only 3 substitute
substitute_3.head(5)
```

```
[388]:
```

	name	total_substitute_counts
12	anovate cream	3
63	af kit tablet	3
82	angispan - tr 2.5mg capsule	3
123	ajaduo 25mg/5mg tablet	3
130	aldosmin 500mg tablet	3

```
[389]: #name of the medicine that has only 4 substitute
substitute_4.head(5)
```

```
[389]:
```

	name	total_substitute_counts
49	asthakind expectorant sugar free	4
54	asthalin respules	4
55	avil injection	4
133	af 150 tablet dt	4
138	amantrel tablet	4

```
[390]: #name of the medicine that has only 5 substitute
substitute_5.head(5)
```

```
[390]:
```

	name	total_substitute_counts
0	augmentin 625 duo tablet	5
1	azithral 500 tablet	5
2	ascoril ls syrup	5
3	alleggra 120mg tablet	5
5	alleggra-m tablet	5

### 5.0.13 Count of Habit-Forming Drugs by Chemical Class

```
[391]: habit_forming_counts_by_chemical_class = df_cleaned[df_cleaned['Habit Forming']_
↳ == 'Yes'].groupby(['Chemical Class'])['Habit Forming'].count().loc[lambda x:
↳ x.index != 'UnKnown']
habit_forming_counts_by_chemical_class = pd.
↳ DataFrame(habit_forming_counts_by_chemical_class).reset_index()
habit_forming_counts_by_chemical_class = habit_forming_counts_by_chemical_class.
↳ rename(columns = {'Habit Forming' : 'Habit-Forming Medications per Chemical_
↳ Class'})
habit_forming_counts_by_chemical_class
```

```
[391]:
```

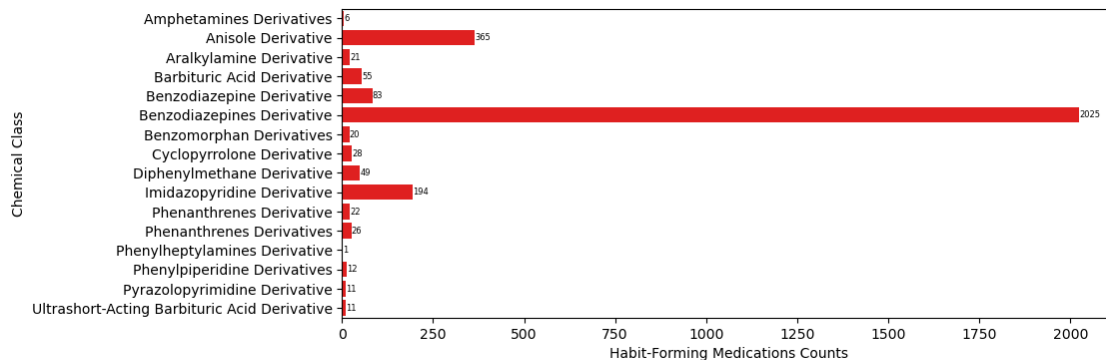
	Chemical Class \
0	Amphetamines Derivatives
1	Anisole Derivative
2	Aralkylamine Derivative
3	Barbituric Acid Derivative
4	Benzodiazepine Derivative
5	Benzodiazepines Derivative
6	Benzomorphan Derivatives
7	Cyclopyrrolone Derivative
8	Diphenylmethane Derivative
9	Imidazopyridine Derivative
10	Phenanthrenes Derivative
11	Phenanthrenes Derivatives
12	Phenylheptylamines Derivative
13	Phenylpiperidine Derivatives
14	Pyrazolopyrimidine Derivative
15	Ultrashort-Acting Barbituric Acid Derivative

	Habit-Forming Medications per Chemical Class
0	6
1	365
2	21
3	55
4	83
5	2025
6	20
7	28
8	49
9	194
10	22
11	26
12	1
13	12
14	11
15	11

```
[392]: plt.figure(figsize=(10,4))
ax = sns.barplot(data=habit_forming_counts_by_chemical_class,y='Chemical_
↳Class',x='Habit-Forming Medications per Chemical Class',color='red')
ax.bar_label(ax.containers[0], fontsize=6)
plt.xlabel('Habit-Forming Medications Counts')
```

```
[392]: Text(0.5, 0, 'Habit-Forming Medications Counts')
```



#### 5.0.14 Count of Habit-Forming Drugs by Action Class

```
[393]: habit_forming_counts_by_action_class = df_cleaned[df_cleaned['Habit Forming']_
↳== 'Yes'].groupby(['Action Class'])['Habit Forming'].count().loc[lamba x:x.
↳index != 'UnKnown']
habit_forming_counts_by_action_class = pd.
↳DataFrame(habit_forming_counts_by_action_class).reset_index()
habit_forming_counts_by_action_class = habit_forming_counts_by_action_class.
↳rename(columns = {'Habit Forming' : 'Habit-Forming Medications per Action_
↳Class'})
habit_forming_counts_by_action_class
```

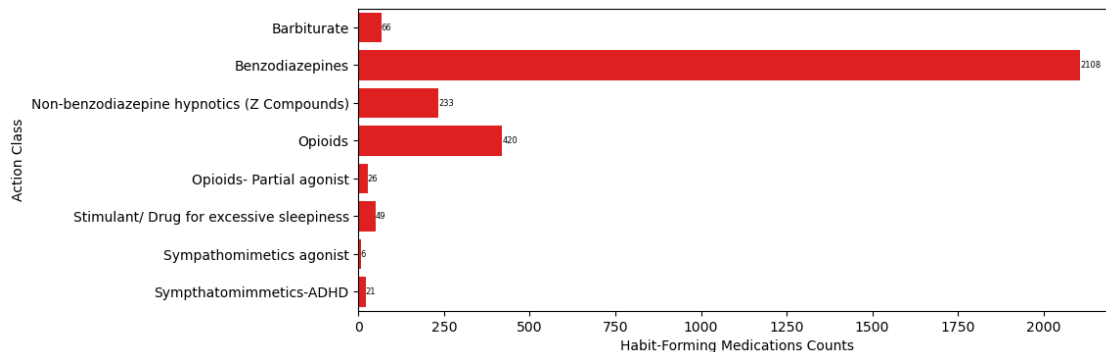
```
[393]:
```

	Action Class \
0	Barbiturate
1	Benzodiazepines
2	Non-benzodiazepine hypnotics (Z Compounds)
3	Opioids
4	Opioids- Partial agonist
5	Stimulant/ Drug for excessive sleepiness
6	Sympathomimetics agonist
7	Sympthatomimmetics-ADHD
	Habit-Forming Medications per Action Class
0	66
1	2108

2	233
3	420
4	26
5	49
6	6
7	21

```
[394]: plt.figure(figsize=(10,4))
ax = sns.barplot(data=habit_forming_counts_by_action_class,y='Action_
↪Class',x='Habit-Forming Medications per Action Class',color='red')
ax.bar_label(ax.containers[0], fontsize=6)
plt.xlabel('Habit-Forming Medications Counts')
```

```
[394]: Text(0.5, 0, 'Habit-Forming Medications Counts')
```



### 5.0.15 Count of Habit-Forming Drugs by Therapeutic Class

```
[395]: habit_forming_counts_by_Therapeutic_class = df_cleaned[df_cleaned['Habit_
↪Forming'] == 'Yes'].groupby(['Therapeutic Class'])['Habit Forming'].count().
↪loc[lambda x:x.index != 'UnKnown']
habit_forming_counts_by_Therapeutic_class = pd.
↪DataFrame(habit_forming_counts_by_Therapeutic_class).reset_index()
habit_forming_counts_by_Therapeutic_class =
↪habit_forming_counts_by_Therapeutic_class.rename(columns = {'Habit Forming' :
↪ 'Habit-Forming Medications per Therapeutic Class'})
habit_forming_counts_by_Therapeutic_class
```

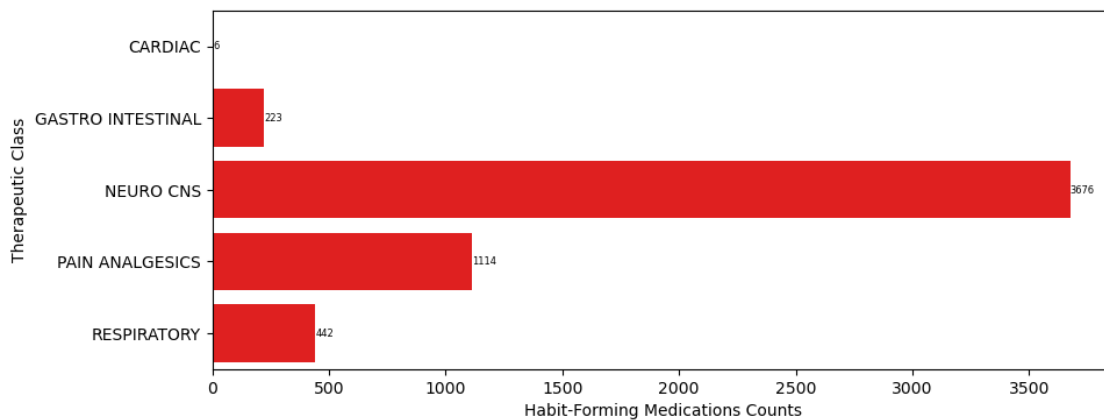
```
[395]:
```

	Therapeutic Class	Habit-Forming Medications per Therapeutic Class
0	CARDIAC	6
1	GASTRO INTESTINAL	223
2	NEURO CNS	3676
3	PAIN ANALGESICS	1114
4	RESPIRATORY	442



```
[396]: plt.figure(figsize=(10,4))
ax = sns.barplot(data=habit_forming_counts_by_Therapeutic_class,y='Therapeutic_
↪Class',x='Habit-Forming Medications per Therapeutic Class',color='red')
ax.bar_label(ax.containers[0], fontsize=6)
plt.xlabel('Habit-Forming Medications Counts')
```

```
[396]: Text(0.5, 0, 'Habit-Forming Medications Counts')
```



#### 5.0.16 Identify the medicine that has less than 5 Side Effects

```
[397]: df_cleaned[df_cleaned['total_side_effect_recorded']<=5][['name','total_side_effect_recorded']]
```

```
[397]:
```

	name	total_side_effect_recorded
0	augmentin 625 duo tablet	3
1	azithral 500 tablet	4
3	allegra 120mg tablet	4
4	avil 25 tablet	2
6	amoxyclav 625 tablet	3
...	...	...
248209	zef cv 200mg/125mg tablet	5
248210	ziyapod 100mg oral suspension	3
248215	zivex 25mg tablet	5
248216	zi fast 500mg injection	5
248217	zyvocol 1% dusting powder	4

```
[104685 rows x 2 columns]
```

### 5.0.17 Discussion And Conclusion :“250k Medicines Usage, Side Effects, and Substitutes”

#### 5.0.18 Project Overview:

The goal of this project was to analyze a dataset that includes detailed information about over 250,000 medicines. This dataset covers attributes such as the drug names, their substitutes, side effects, therapeutic uses, chemical classes, and more. By analyzing this data, I aimed to identify patterns in medicine usage, common side effects, and the availability of substitutes, with the ultimate goal of gaining insights that can be useful in pharmaceutical research, healthcare, and drug safety.

#### 5.0.19 Step-by-Step Analysis:

1. **Data Loading and Initial Exploration:** I started by loading the dataset using Python (with Pandas) and conducted an initial inspection. This step involved:
  - Checking the basic structure of the dataset.
  - Identifying columns and their data types.
  - Reviewing the first few rows to get a sense of the data.
2. **Data Cleaning:** In this step, I addressed missing values and inconsistencies:
  - I filled missing data with “Unknown” or removed rows/columns that contained too many missing values.
  - This ensured that the analysis could proceed without errors or bias due to missing data.
  - I also removed duplicates to maintain data integrity and normalized text columns (e.g., lowercasing and stripping whitespace) for consistency.
3. **Substitute Analysis:** I analyzed the availability of substitutes for each medicine:
  - I counted how many substitutes each drug had by considering the columns for substitute names.
  - I explored the top medicines with the most substitutes to understand which drugs have readily available alternatives.
  - This is valuable in understanding the drug market and providing patients with more treatment options.
4. **Side Effect Analysis:** Side effects were another key focus:
  - I combined the various columns for side effects (up to 41 different columns) into one to assess the frequency of each side effect.
  - I identified the most common side effects across all medicines, such as nausea, vomiting, diarrhea, and abdominal pain, which could indicate general trends in medication safety.
  - This analysis helps in pharmacovigilance by identifying patterns in adverse reactions.
5. **Use Case Analysis:** I explored the therapeutic uses of the medicines by:
  - Combining the columns for different uses (up to 5 different uses per drug) and identifying the most common treatments provided by these medicines.
  - I found that conditions such as bacterial infections, pain relief, and type 2 diabetes treatment were among the most frequent.
  - This analysis provides insights into the most prevalent conditions treated by the pharmaceutical industry.
6. **Classification Analysis:** To better understand patterns in drug properties, I grouped medicines based on:
  - **Chemical Class:** Medicines with similar chemical structures were grouped, and I analyzed how side effects varied across these groups.

- **Therapeutic Class:** I classified medicines according to their therapeutic uses (e.g., respiratory, anti-infectives).
  - **Action Class:** Medicines were also grouped by their actions (e.g., H2 receptor blockers), and I examined the side effects associated with these classes.
  - This classification allowed I to identify trends and similarities across medicines with similar intended purposes or mechanisms.
7. **Visualization:** To enhance the understanding of Ir findings, I created visualizations:
- I used tools like Matplotlib and Seaborn to visualize distributions, correlations, and patterns in side effects, substitutes, and usage.
  - This provided clear, interpretable results for stakeholders in drug research or healthcare.
8. **Advanced Analysis (Optional):**
- The project suggests further exploration using clustering or machine learning techniques, such as building models to predict side effects based on the chemical or therapeutic class of a medicine.
  - This could help in automating the process of identifying potential adverse reactions, thus aiding drug development and safety protocols.

### 5.0.20 Conclusion:

The project successfully explored the relationships between medicines, their substitutes, side effects, and therapeutic uses. Key findings included identifying the most common side effects (such as nausea, diarrhea, and vomiting), recognizing medicines with the most substitutes, and analyzing the variation of these factors across different chemical, therapeutic, and action classes. The insights derived from this project are valuable for drug safety, healthcare planning, and research in the pharmaceutical industry.

This analysis could be extended with more advanced techniques such as clustering, predictive modeling, and deeper exploration of correlations between drug classes and their effects, helping to refine drug recommendations or safety guidelines.

[ ]: