3108 lines (3108 loc) · 814 KB

1. Business Understanding

1.1 Overview

The third Sustainable Development Goal is focused on ensuring healthy lives and promoting well-being for all at all ages. It proposes to end the preventable death of newborns, infants and children under five (child mortality) and end epidemics. Under the goal, the United Nations set 13 targets to help reach this goal of promoting good health and well-being like achieving universal health coverage, supporting research, development and universal access to affordable vaccines and medicines, etc. These targets are indicators for measuring the success of the goal. The goal is to achieve universal health coverage and equitable access of healthcare services to all.

1.2 Problem Statement

Recent evidence suggests the Kenyan healthcare system performs poorly as anywhere between 20% and 50% of the resources devoted to health in Kenya are used inefficiently. This inefficiency significantly hampers healthcare accessibility and quality, particularly in Nairobi, Kenya

1.3 Primary Objective

The objective of this data science project is to analyse and derive insights from data of healthcare facilities and the population of Nairobi.

2. Data Understanding

Two datasets were provided. The first dataset on healthcare facilities, this data was collected between October 2015 and November 2023. The data will be extracted from the opendataAfrica website, an API is provided to extract the data for an analysis. The data includes a comprehensive list of health facilities in Kenya, complete with services offered as well as granular geo-data (Provincial, County, District, Location, Sub-Location and Division information) The second dataset presents the distribution of enumerated population by single year and five-year age groups, sex and administrative unit (county and sub-county). The data was provided the Kenya National Bureau of Statistics(KNBS) from Kenya's 6th National Census i.e. The 2019 Kenya Population and Housing Census

This phase is broken down into four tasks that include;

- Collection of the Initial Data
- Data Description
- Data Cleaning
- Exploratory Data Analysis

2.1 Data Overview

2.1.1 Loading the dataset

In [2]:
```
#import the necessary libraries

## Libraries for loading the dataset
import requests
import json

## FOr data analysis and preparation
import pandas as pd
import numpy as np

## For data visualisation
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
```

In [3]:
```
# Define the URL to access the data
url = 'https://open.africa/dataset/3e95b5cb-39f5-44d3-94b6-f2d5285b0478/resourc

# Send a GET request to the URL and retrieve the response
response = requests.get(url)

#Ignore any warning that may occur
#warnings.filterwarnings('ignore', message=".*SSCS size is 0 but SSAT size is n

# Save the content to a file
with open('ehealth_data.xls', 'wb') as f:
    f.write(response.content)

# Read the Excel file into a DataFrame
facilities_df = pd.read_excel('ehealth_data.xls')

# Print the DataFrame
print(facilities_df)
```

```
WARNING *** OLE2 inconsistency: SSCS size is 0 but SSAT size is non-zero
       Facility Code                                Facility Name  \
0              19224                      CDF Kiriari Dispensary
1              19310   St Jude's Huruma Community Health Services
2              14180                           10 Engineer VCT
3              17486                              12 Engineers
4              18393            3Kl Maternity & Nursing Home
...              ...                                          ...
10500          17220                                   Ziwa SDA
10501          15788              Ziwa Sub-District Hospital
10502          11915                       Ziwani Dispensary
10503          16997                Zombe Catholic Dispensary
10504          20313                     Zombe medical clinic

          Province        County       District            Division  \
```

```
0          Eastern          Embu       Manyatta            Manyatta
1          Nairobi       Nairobi        Mathare             Huruma
2      Rift Valley      Laikipia  Laikipia East            Central
3          Central        Kiambu     Thika West                NaN
4      Rift Valley       Kajiado  Kajiado North      Ongata Rongai
...            ...           ...            ...                ...
10500  Rift Valley   Uasin Gishu   Eldoret West                Soy
10501  Rift Valley   Uasin Gishu   Eldoret West                Soy
10502        Coast  Taita Taveta         Taveta            Challa
10503      Eastern         Kitui         Mutitu  zombe/mwitika ward
10504      Eastern         Kitui         Mutitu  zombe/mwitika ward

                      Type                                        Owner  \
0                Dispensary                             Ministry of Health
1             Medical Clinic                  Private Practice - Unspecified
2                Dispensary                                  Armed Forces
3                Dispensary                             Ministry of Health
4              Nursing Home               Private Practice - Clinical Officer
...                     ...                                           ...
10500            Dispensary            Christian Health Association of Kenya
10501  Sub-District Hospital                             Ministry of Health
10502            Dispensary                 Private Enterprise (Institution)
10503            Dispensary  Kenya Episcopal Conference-Catholic Secretariat
10504         Medical Clinic               Private Practice - Clinical Officer

      Location Sub Location  ...  IPD OPD OUTREACH  PMTCT  RAD/XRAY RHTC/RHDC  \
0       Ruguru       Ruguru  ...  NaN NaN      NaN    NaN       NaN       NaN
1       Huruma       Huruma  ...  NaN NaN      NaN    NaN       NaN       NaN
2      Nanyuki      Majengo  ...  NaN NaN      NaN    NaN       NaN       NaN
3          NaN          NaN  ...  NaN NaN      NaN    NaN       NaN       NaN
4       Gataka       Gataka  ...  NaN NaN      NaN    NaN       NaN       NaN
...        ...          ...  ...  ...  ..      ...    ...       ...       ...
10500     Ziwa      Sirikwa  ...  NaN NaN      NaN    NaN       NaN       NaN
10501  Sirikwa      Sirikwa  ...    Y NaN      NaN    NaN       NaN       NaN
10502   Challa       Ziwani  ...    Y NaN      NaN    NaN       NaN       NaN
10503    Zombe         Thua  ...  NaN NaN      NaN    NaN       NaN       NaN
10504    Zombe     Malalani  ...  NaN NaN      NaN    NaN       NaN       NaN

      TB DIAG TB LABS TB TREAT YOUTH
0         NaN     NaN      NaN   NaN
1         NaN     NaN      NaN   NaN
2         NaN     NaN      NaN   NaN
3         NaN     NaN      NaN   NaN
4         NaN     NaN      NaN   NaN
...       ...     ...      ...   ...
10500     NaN     NaN      NaN   NaN
10501     NaN     NaN      NaN   NaN
10502     NaN     NaN      NaN   NaN
10503     NaN     NaN      NaN   NaN
10504     NaN     NaN      NaN   NaN

[10505 rows x 50 columns]
```

We can see there is some regions included that are not in Nairobi, let's categorize them and analyses only the heathcare facilities in Nairobi

In [4]:

```
# Filtering the data to Nairob Province only
Nairobi = facilities_df['Province'] == 'Nairobi'
Nairobi_df = facilities_df[Nairobi]
print(Nairobi_df)
```

```
      Facility Code                                Facility Name Province  \
1             19310   St Jude's Huruma Community Health Services  Nairobi
7             13043                         7Kr Mrs Health Centre  Nairobi
10            20346                       AAR Adams Health Centre  Nairobi
11            12861                        AAR City Centre Clinic  Nairobi
12            16796           AAR Clinic Sarit Centre (Westlands)  Nairobi
...             ...                                          ...      ...
10459         13260                      Woodstreet Nursing Home  Nairobi
10493         19273                    Zimerbreeze Medical Centre  Nairobi
10494         19378                             Zimma Health Care  Nairobi
10495         13261                  Zimmerman Medical Dispensary  Nairobi
10496         13262                               Zinduka Clinic  Nairobi

       County   District         Division                     Type  \
1      Nairobi    Mathare           Huruma            Medical Clinic
7      Nairobi    Langata         Lang'ata             Health Centre
10     Nairobi      Kibra           Woodly            Medical Clinic
11     Nairobi    Starehe          Starehe            Medical Clinic
12     Nairobi  Westlands        Parklands            Medical Clinic
...        ...        ...              ...                      ...
10459  Nairobi  Kamukunji  Eastleigh North              Nursing Home
10493  Nairobi   Roysambu         Kasarani            Medical Clinic
10494  Nairobi   Roysambu         Kasarani            Medical Clinic
10495  Nairobi    Ruaraka         Kasarani                Dispensary
10496  Nairobi    Langata          Langata  VCT Centre (Stand-Alone)

                                      Owner                   Location  \
1              Private Practice - Unspecified                     Huruma
7                                Armed Forces                   Mugumoini
10     Private Practice - General Practitioner                     Woodly
11            Private Enterprise (Institution)  Central Business District
12            Private Enterprise (Institution)                  Parklands
...                                        ...                        ...
10459         Private Enterprise (Institution)        Eastleigh Section I
10493  Private Practice - General Practitioner                    Gthurai
10494  Private Practice - General Practitioner                    Githurai
10495         Private Enterprise (Institution)                    Githurai
10496                        Other Faith Based               Nairobi West

          Sub Location  ...  IPD OPD OUTREACH  PMTCT  RAD/XRAY RHTC/RHDC  \
1              Huruma  ...  NaN NaN      NaN    NaN       NaN       NaN
7           Mugumoini  ...    Y NaN      NaN    NaN       NaN       NaN
10             Woodly  ...  NaN NaN      NaN    NaN       NaN       NaN
11                NaN  ...    Y NaN      NaN    NaN       NaN       NaN
12     Upper Parklands  ...  NaN NaN      NaN    NaN       NaN       NaN
...                ...  ...  ...  ..      ...    ...       ...       ...
10459              NaN  ...    Y NaN      NaN    NaN       NaN       NaN
10493         Zimerman  ...  NaN NaN      NaN    NaN       NaN       NaN
10494        zimmerman  ...  NaN NaN      NaN    NaN       NaN       NaN
10495              NaN  ...    Y NaN      NaN    NaN       NaN       NaN
10496              NaN  ...  NaN NaN      NaN    NaN       NaN       NaN

      TB DIAG TB LABS TB TREAT YOUTH
1         NaN     NaN      NaN   NaN
7         NaN     NaN      NaN   NaN
10        NaN     NaN      NaN   NaN
11        NaN     NaN      NaN   NaN
12        NaN     NaN      NaN   NaN
...       ...     ...      ...   ...
10459     NaN     NaN      NaN   NaN
```

```
10493     NaN     NaN      NaN   NaN
10494     NaN     NaN      NaN   NaN
10495     NaN     NaN      NaN   NaN
10496     NaN     NaN      NaN   NaN

[942 rows x 50 columns]
```

We have an additional dataset on population by age, sex and county

In [5]:
```
import pandas as pd

# URL of the dataset
url = "https://open.africa/dataset/9b94fe50-9d75-4b92-be00-6354c6e6cc88/resourc

# Read the CSV file into a pandas DataFrame
population_df = pd.read_csv(url)

# Display the first few rows of the DataFrame
print(population_df)
```

```
           county  sub-county         Age    Male  Female   Total
0         BARINGO         ALL       Total  336322  330428  666750
1         BARINGO         ALL           0    8303    7982   16285
2         BARINGO         ALL           1    8669    8417   17086
3         BARINGO         ALL           2   10226    9762   19988
4         BARINGO         ALL           3   10265   10086   20351
...           ...         ...         ...     ...     ...     ...
48203  WEST POKOT  WEST POKOT          98       6       5      11
48204  WEST POKOT  WEST POKOT          99       3      17      20
48205  WEST POKOT  WEST POKOT       95-99      18      52      70
48206  WEST POKOT  WEST POKOT        100+      15      39      54
48207  WEST POKOT  WEST POKOT  Not Stated       1       1       2

[48208 rows x 6 columns]
```

We only want the data on the population only based in Nairobi county. Lets then categorize this data set

In [6]:
```
Nairobipop = population_df['county'] == 'NAIROBI'
Nairobi_pop_df = population_df[Nairobipop]
print(Nairobi_pop_df.head(25))
```

```
       county sub-county     Age     Male   Female    Total
31604  NAIROBI        ALL   Total  2192452  2204376  4396828
31605  NAIROBI        ALL       0    57265    56523   113788
31606  NAIROBI        ALL       1    56019    54601   110620
31607  NAIROBI        ALL       2    52518    51848   104366
31608  NAIROBI        ALL       3    51115    51027   102142
31609  NAIROBI        ALL       4    47182    46889    94071
31610  NAIROBI        ALL   0 - 4   264099   260888   524987
31611  NAIROBI        ALL       5    45203    44711    89914
31612  NAIROBI        ALL       6    43635    44226    87861
31613  NAIROBI        ALL       7    43507    43655    87162
31614  NAIROBI        ALL       8    40916    41615    82531
31615  NAIROBI        ALL       9    41969    43275    85244
31616  NAIROBI        ALL     5-9   215230   217482   432712
31617  NAIROBI        ALL      10    40791    40892    81683
```

```
31618  NAIROBI        ALL      11    35581    37513    73094
31619  NAIROBI        ALL      12    37907    39622    77529
31620  NAIROBI        ALL      13    36701    39479    76180
31621  NAIROBI        ALL      14    34028    36036    70064
31622  NAIROBI        ALL  10 -14   185008   193542   378550
31623  NAIROBI        ALL      15    30919    35136    66055
31624  NAIROBI        ALL      16    30408    35599    66007
31625  NAIROBI        ALL      17    32413    37865    70278
31626  NAIROBI        ALL      18    29102    36415    65517
31627  NAIROBI        ALL      19    36256    47740    83996
31628  NAIROBI        ALL   15-19   159098   192755   351853
```

2.1.2 Data Description

First let's look at the data on the *healthcare facilities* in Nairobi

In [7]:

```
## Checking the information about the dataframe
Nairobi_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 942 entries, 1 to 10496
Data columns (total 50 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Facility Code            942 non-null    int64  
 1   Facility Name            942 non-null    object 
 2   Province                 942 non-null    object 
 3   County                   942 non-null    object 
 4   District                 942 non-null    object 
 5   Division                 914 non-null    object 
 6   Type                     942 non-null    object 
 7   Owner                    942 non-null    object 
 8   Location                 894 non-null    object 
 9   Sub Location             672 non-null    object 
 10  Description of Location  641 non-null    object 
 11  Constituency             942 non-null    object 
 12  Nearest Town             824 non-null    object 
 13  Beds                     942 non-null    float64
 14  Cots                     942 non-null    float64
 15  Official Landline        197 non-null    object 
 16  Official Fax             19 non-null     object 
 17  Official Mobile          305 non-null    object 
 18  Official Email           222 non-null    object 
 19  Official Address         412 non-null    object 
 20  Official Alternate No    157 non-null    float64
 21  Town                     434 non-null    object 
 22  Post Code                397 non-null    object 
 23  In Charge                592 non-null    object 
 24  Job Title of in Charge   553 non-null    object 
 25  Open 24 Hours            931 non-null    object 
 26  Open Weekends            933 non-null    object 
 27  Operational Status       942 non-null    object 
 28  ANC                      0 non-null      float64
 29  ART                      109 non-null    object 
 30  BEOC                     0 non-null      float64
 31  BLOOD                    0 non-null      float64
 32  CAES SEC                 0 non-null      float64
 33  CEOC                     0 non-null      float64
 34  C-IMCI                   72 non-null     object 
```

```
 35  EPI                     0 non-null      float64
 36  FP                      280 non-null    object
 37  GROWM                   0 non-null      float64
 38  HBC                     250 non-null    object
 39  HCT                     0 non-null      float64
 40  IPD                     297 non-null    object
 41  OPD                     0 non-null      float64
 42  OUTREACH                0 non-null      float64
 43  PMTCT                   0 non-null      float64
 44  RAD/XRAY                0 non-null      float64
 45  RHTC/RHDC               0 non-null      float64
 46  TB DIAG                 0 non-null      float64
 47  TB LABS                 0 non-null      float64
 48  TB TREAT                0 non-null      float64
 49  YOUTH                   0 non-null      float64
dtypes: float64(20), int64(1), object(29)
memory usage: 375.3+ KB
```

In [8]:

```
#Checking the names of the columns and their types in the dataframe
Nairobi_df.columns
Nairobi_df.dtypes
```

Out[8]:

```
Facility Code               int64
Facility Name              object
Province                   object
County                     object
District                   object
Division                   object
Type                       object
Owner                      object
Location                   object
Sub Location               object
Description of Location    object
Constituency               object
Nearest Town               object
Beds                      float64
Cots                      float64
Official Landline          object
Official Fax               object
Official Mobile            object
Official Email             object
Official Address           object
Official Alternate No     float64
Town                       object
Post Code                  object
In Charge                  object
Job Title of in Charge     object
Open 24 Hours              object
Open Weekends              object
Operational Status         object
ANC                       float64
ART                        object
BEOC                      float64
BLOOD                     float64
CAES SEC                  float64
CEOC                      float64
C-IMCI                     object
EPI                       float64
FP                         object
GROWM                     float64
```

```
HBC                    object
HCT                   float64
IPD                    object
OPD                   float64
OUTREACH              float64
PMTCT                 float64
RAD/XRAY              float64
RHTC/RHDC             float64
TB DIAG               float64
TB LABS               float64
TB TREAT              float64
YOUTH                 float64
dtype: object
```

In [9]:
```
#Let's have a look at the descriptive statistics of the numerical columns
Nairobi_df.describe()
```

Out[9]:

	Facility Code	Beds	Cots	Official Alternate No	ANC	BEOC	BLOOD	CAE SE
count	942.000000	942.000000	942.000000	1.570000e+02	0.0	0.0	0.0	0.
mean	16799.744161	7.787686	1.152866	6.498035e+08	NaN	NaN	NaN	Na
std	3129.912948	58.966655	15.196691	5.890122e+08	NaN	NaN	NaN	Na
min	12861.000000	0.000000	0.000000	2.222575e+06	NaN	NaN	NaN	Na
25%	13112.250000	0.000000	0.000000	7.103701e+08	NaN	NaN	NaN	Na
50%	18346.000000	0.000000	0.000000	7.225878e+08	NaN	NaN	NaN	Na
75%	19492.750000	1.000000	0.000000	7.288983e+08	NaN	NaN	NaN	Na
max	21281.000000	1455.000000	427.000000	7.329109e+09	NaN	NaN	NaN	Na

8 rows × 21 columns

In [10]:
```
#Checking the statistics of the columns with the dtype `object`
Nairobi_df.describe(include='O')
```

Out[10]:

	Facility Name	Province	County	District	Division	Type	Owner	Location	Lo
count	942	942	942	942	914	942	942	894	
unique	941	1	1	17	89	20	21	153	
top	St Mary's Medical Clinic	Nairobi	Nairobi	Starehe	Kasarani	Medical Clinic	Private Enterprise (Institution)	Central	
freq	2	942	942	136	105	460	219	59	

4 rows × 29 columns

4 rows × 29 columns

- We see there are 941 healthcare facilities, 917 operational in Nairobi in 17 districts and 20 types of healthcare facilities, 460 of them being medical clinics.
- Many of the healthcare facilities are private institutions.

Next, let's look at the dataset that involves the *population* of Nairobi county

In [11]:
```
## Checking the information about the dataframe
Nairobi_pop_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1476 entries, 31604 to 33079
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   county      1476 non-null   object
 1   sub-county  1476 non-null   object
 2   Age         1476 non-null   object
 3   Male        1476 non-null   object
 4   Female      1476 non-null   object
 5   Total       1476 non-null   object
dtypes: object(6)
memory usage: 80.7+ KB
```

In [12]:
```
#Checking the names of the columns and their types in the dataframe
Nairobi_pop_df.columns
Nairobi_pop_df.dtypes
```

Out[12]:
```
county        object
sub-county    object
Age           object
Male          object
Female        object
Total         object
dtype: object
```

In [13]:
```
#Let's have a look at the descriptive statistics of the numerical columns
Nairobi_pop_df.describe()
```

Out[13]:

	county	sub-county	Age	Male	Female	Total
count	1476	1476	1476	1476	1476	1476
unique	1	12	123	1112	1106	1206
top	NAIROBI	ALL	Total	1	3	5
freq	1476	123	12	27	18	13

In [14]:
```
#Checking the statistics of the columns with the dtype `object`
Nairobi_pop_df.describe(include='O')
```

Out[14]:

	county	sub-county	Age	Male	Female	Total
count	1476	1476	1476	1476	1476	1476
unique	1	12	123	1112	1106	1206
top	NAIROBI	ALL	Total	1	3	5
freq	1476	123	12	27	18	13

This dataset gives on info on the number of people in Nairobi according to their age, gender and subcounty

2.2 Data Preparation

This is the actual preparation of the data to allow data analysis, it involves, data cleaning and formatting to ensure the Validity, Accuracy, Completeness, Consistency and Uniformity of the Data.

This will include checking for missing and duplicated values and values.

In [15]:

```
# Checking for missing values in the dataset involving healthcare facilities
Nairobi_df.isnull().sum()
```

Out[15]:

```
Facility Code               0
Facility Name               0
Province                    0
County                      0
District                    0
Division                   28
Type                        0
Owner                       0
Location                   48
Sub Location              270
Description of Location   301
Constituency                0
Nearest Town              118
Beds                        0
Cots                        0
Official Landline         745
Official Fax              923
Official Mobile           637
Official Email            720
Official Address          530
Official Alternate No     785
Town                      508
Post Code                 545
In Charge                 350
Job Title of in Charge    389
Open 24 Hours              11
Open Weekends               9
Operational Status          0
ANC                       942
ART                       833
BEOC                      942
BLOOD                     942
```

```
CAES SEC                    942
CEOC                        942
C-IMCI                      870
EPI                         942
FP                          662
GROWM                       942
HBC                         692
HCT                         942
IPD                         645
OPD                         942
OUTREACH                    942
PMTCT                       942
RAD/XRAY                    942
RHTC/RHDC                   942
TB DIAG                     942
TB LABS                     942
TB TREAT                    942
YOUTH                       942
dtype: int64
```

There are number of missing values. We won't be removing the missing values, because we might be removing important information vital to the analysis.

In [16]:
```
#Checking for duplicated values in the rows
Nairobi_df.duplicated().sum()
```

Out[16]:
```
0
```

There are no duplicated values in the data

In [17]:
```
# Checking for missing values in the dataset involving healthcare facilities
Nairobi_pop_df.isnull().sum()
```

Out[17]:
```
county        0
sub-county    0
Age           0
Male          0
Female        0
Total         0
dtype: int64
```

In [18]:
```
#Checking for duplicated values in the rows
Nairobi_pop_df.duplicated().sum()
```

Out[18]:
```
0
```

There are neither any missing values and duplicated values in the population dataset.

2.3 Exploratory Data Analysis

*** We will explore the data on healthcare facilites in Nairobi

2.3.1 Univariate Analysis

The purpose of the univariate analysis is to understand the distribution of values for a single variable.

In [19]:
```
# Count the number of healthcare facilities by type
facility_count_by_type = Nairobi_df.groupby('Type').size().reset_index(name='Co

# Count the number of healthcare facilities by owner
facility_count_by_owner = Nairobi_df.groupby('Owner').size().reset_index(name='

# Count the number of healthcare facilities by operational status
facility_count_by_status = Nairobi_df.groupby('Operational Status').size().rese

# Print the results
print("Number of healthcare facilities by type:")
print(facility_count_by_type)

print("\nNumber of healthcare facilities by owner:")
print(facility_count_by_owner)

print("\nNumber of healthcare facilities by operational status:")
print(facility_count_by_status)
```

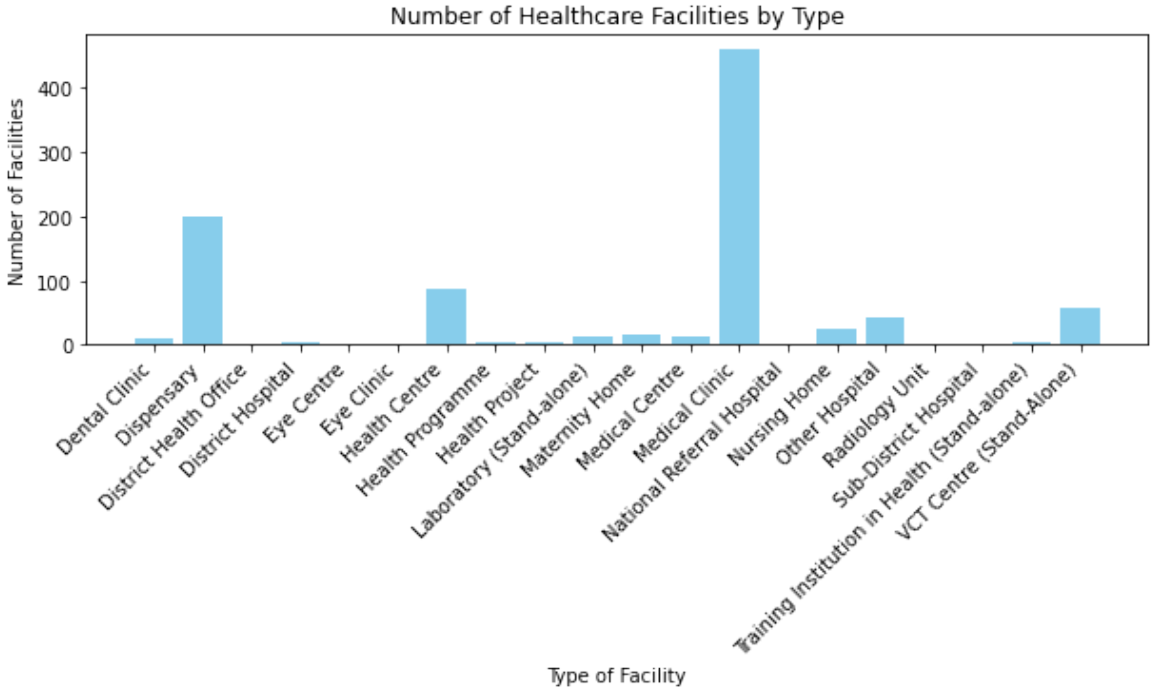
```
Number of healthcare facilities by type:
                                          Type  Count
0                                Dental Clinic     10
1                                   Dispensary    199
2                        District Health Office      1
3                             District Hospital      3
4                                   Eye Centre      2
5                                   Eye Clinic      1
6                                Health Centre     88
7                             Health Programme      5
8                               Health Project      3
9                    Laboratory (Stand-alone)     13
10                              Maternity Home     15
11                              Medical Centre     12
12                              Medical Clinic    460
13                  National Referral Hospital      2
14                                Nursing Home     25
15                              Other Hospital     41
16                              Radiology Unit      1
17                       Sub-District Hospital      1
18  Training Institution in Health (Stand-alone)      4
19                      VCT Centre (Stand-Alone)     56

Number of healthcare facilities by owner:
                                        Owner  Count
0                      Academic (if registered)      6
1                                 Armed Forces      9
2          Christian Health Association of Kenya     24
3                                   Community     11
4                       Company Medical Service      3
5                         Humanitarian Agencies      3
6   Kenya Episcopal Conference-Catholic Secretariat     49
7                               Local Authority     58
8                            Ministry of Health     56
9                 Non-Governmental Organizations    116
10                              Other Faith Based     26
```

```
11                          Other Public Institution     13
12                                        Parastatal      7
13                  Private Enterprise (Institution)    219
14              Private Practice - Clinical Officer      39
15          Private Practice - General Practitioner     161
16            Private Practice - Medical Specialist      34
17               Private Practice - Nurse / Midwife      40
18                   Private Practice - Unspecified      63
19                                State Coorporation      3
20                Supreme Council for Kenya Muslims      2

Number of healthcare facilities by operational status:
  Operational Status  Count
0    Not-Operational     19
1        Operational    917
2    Pending Opening      6
```

In [20]:

```
# Plot bar chart for facility count by type
plt.figure(figsize=(10, 3))
plt.bar(facility_count_by_type['Type'], facility_count_by_type['Count'], color=
plt.xlabel('Type of Facility')
plt.ylabel('Number of Facilities')
plt.title('Number of Healthcare Facilities by Type')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

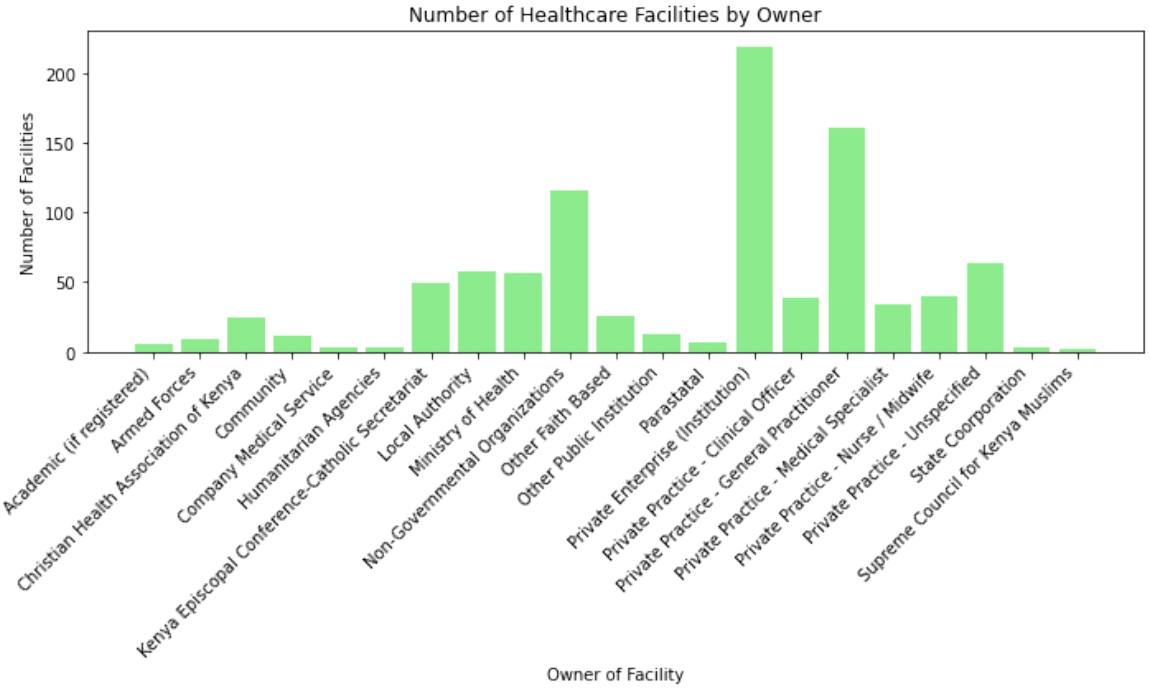
```
C:\Users\HP\AppData\Local\Temp\ipykernel_16868\914183466.py:8: UserWarning: Tight
layout not applied. The bottom and top margins cannot be made large enough to acc
ommodate all axes decorations.
  plt.tight_layout()
```



In [21]:

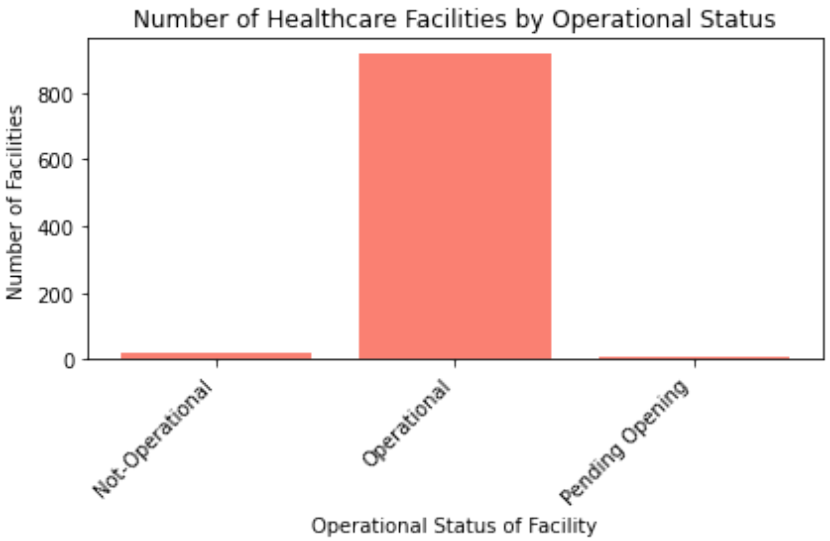
```
# Plot bar chart for facility count by owner
plt.figure(figsize=(10, 6))
plt.bar(facility_count_by_owner['Owner'], facility_count_by_owner['Count'], col
plt.xlabel('Owner of Facility')
plt.ylabel('Number of Facilities')
```

```
plt.ylabel('Number of Facilities')
plt.title('Number of Healthcare Facilities by Owner')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



In [22]:

```
# Plot bar chart for facility count by operational status
plt.figure(figsize=(6, 4))
plt.bar(facility_count_by_status['Operational Status'], facility_count_by_statu
plt.xlabel('Operational Status of Facility')
plt.ylabel('Number of Facilities')
plt.title('Number of Healthcare Facilities by Operational Status')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



- The type of healthcare facilities with the high number is the medical clinics(460)

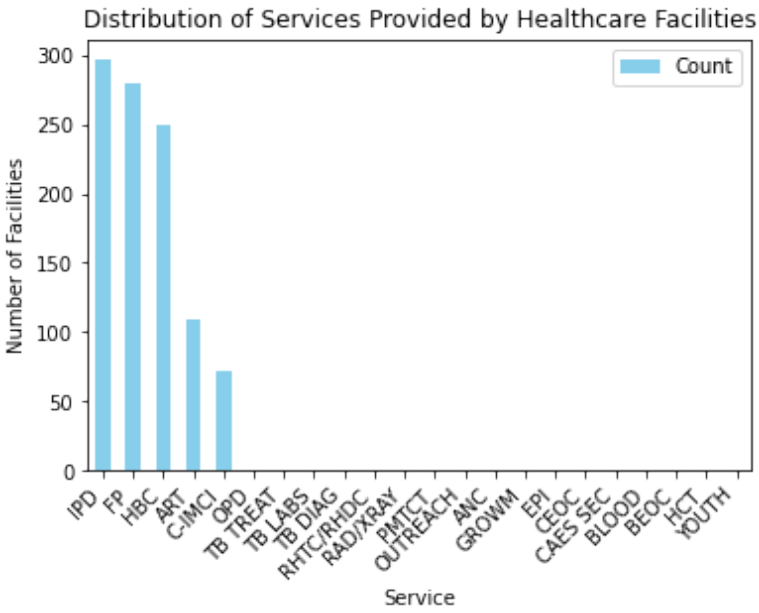
- The type of healthcare facilities with the high number is the medical clinics(460), followed by dispensaries(199)
- Most of the healthcare facilities in Nairobi are owned by private enterprises(219), followed by Private Practice - General Practitioners(161), and the Supreme Council for Kenya Muslims(2)
- 917 facilities are operational, 19 are not and 6 are pending opening.

In [23]:

```
###Lets explore the services offered by these healthcare facilities

# Define a list of services to analyze
services = ['ANC', 'ART', 'HCT', 'FP', 'BEOC', 'BLOOD', 'CAES SEC', 'CEOC', 'C-
            'IPD', 'OPD', 'OUTREACH', 'PMTCT', 'RAD/XRAY', 'RHTC/RHDC', 'TB DIA

# Initialize an empty dictionary to store the count of facilities offering each
service_counts = {}

# Iterate over each service
for service in services:
    # Count the number of facilities offering the current service
    count = Nairobi_df[service].dropna().shape[0]  # Drop NA values and count n
    # Store the count in the dictionary
    service_counts[service] = count

# Convert the counts dictionary to a DataFrame for better visualization
service_counts_df = pd.DataFrame.from_dict(service_counts, orient='index', colu

# Sort the DataFrame by count in descending order
service_counts_df = service_counts_df.sort_values(by='Count', ascending=False)

# Print the distribution of services provided
print("Distribution of different services provided by healthcare facilities:")
print(service_counts_df)

# Plot a bar chart to visualize the distribution of services provided
plt.figure(figsize=(12, 14))
service_counts_df.plot(kind='bar', color='skyblue')
plt.xlabel('Service')
plt.ylabel('Number of Facilities')
plt.title('Distribution of Services Provided by Healthcare Facilities')
plt.xticks(rotation=45, ha='right')
plt.show()
```

```
Distribution of different services provided by healthcare facilities:
           Count
IPD          297
FP           280
HBC          250
ART          109
C-IMCI        72
OPD            0
TB TREAT       0
TB LABS        0
TB DIAG        0
RHTC/RHDC      0
RAD/XRAY       0
PMTCT          0
OUTREACH       0
```

```
ANC             0
GROWM           0
EPI             0
CEOC            0
CAES SEC        0
BLOOD           0
BEOC            0
HCT             0
YOUTH           0
<Figure size 864x1008 with 0 Axes>
```



The service that is offered by most healthcare facilities is Inpatient Care followed by Family Planning.

2.3.2 Bivariate Analysis

Bivariate analysis is the analysis of exactly two variables. We will use bivariate analysis to find relationships between two variables.

In [45]:

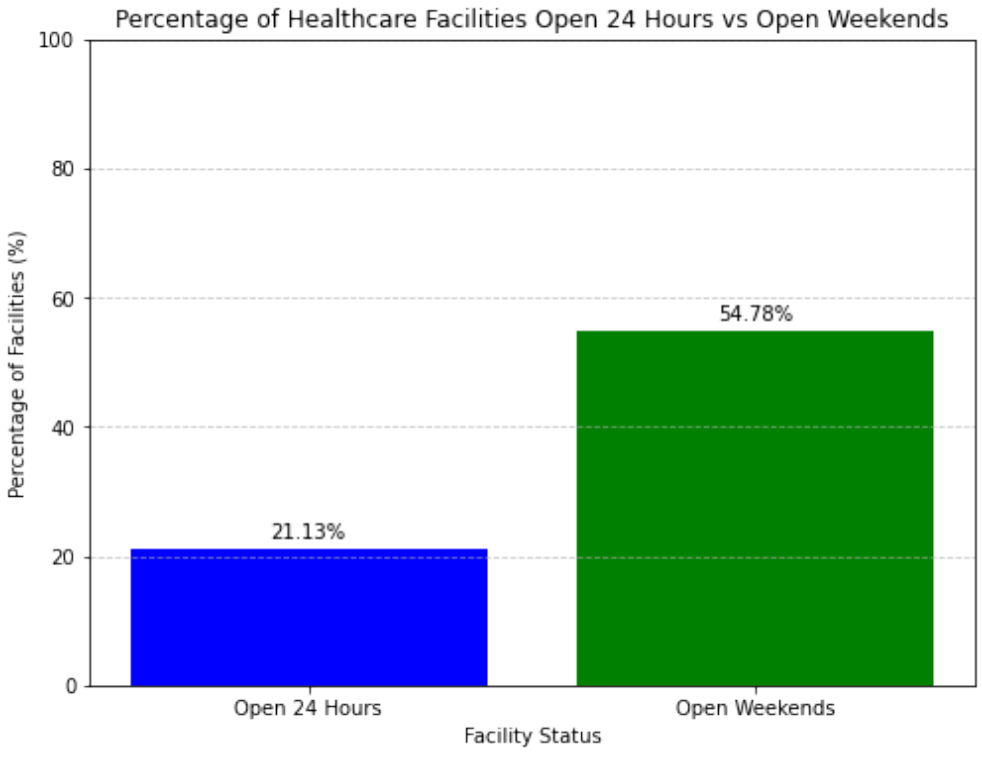
```
### Let's compare the facilities than open 2 hours and that open on the weekend

# Filter the DataFrame for facilities that are open 24 hours
open_24_hours_facilities = Nairobi_df[Nairobi_df['Open 24 Hours'] == 'Y'].shape
# Print the details of facilities that are open 24 hours
print("Healthcare facilities that are open 24 hours:", open_24_hours_facilities


# Filter the DataFrame for facilities that are open 24 hours
open_weekends_facilities = Nairobi_df[Nairobi_df['Open Weekends'] == 'Y'].shape
# Print the details of facilities that are open 24 hours
print("Healthcare facilities that are open on weekends:", open_weekends_facilit

# Calculate the total number of facilities
total_facilities = Nairobi_df.shape[0]

# Calculate the percentage of facilities that are open 24 hours
percentage_open_24_hours = (open_24_hours_facilities / total_facilities) * 100

# Calculate the percentage of facilities that are open weekends
```

```
# Calculate the percentage of facilities that are open weekends
percentage_open_weekends = (open_weekends_facilities / total_facilities) * 100

# Print the results
print("Percentage of facilities open 24 hours: {:.2f}%".format(percentage_open_
print("Percentage of facilities open weekends: {:.2f}%".format(percentage_open_
```

```
Healthcare facilities that are open 24 hours: 199
Healthcare facilities that are open on weekends: 516
Percentage of facilities open 24 hours: 21.13%
Percentage of facilities open weekends: 54.78%
```

In [25]:

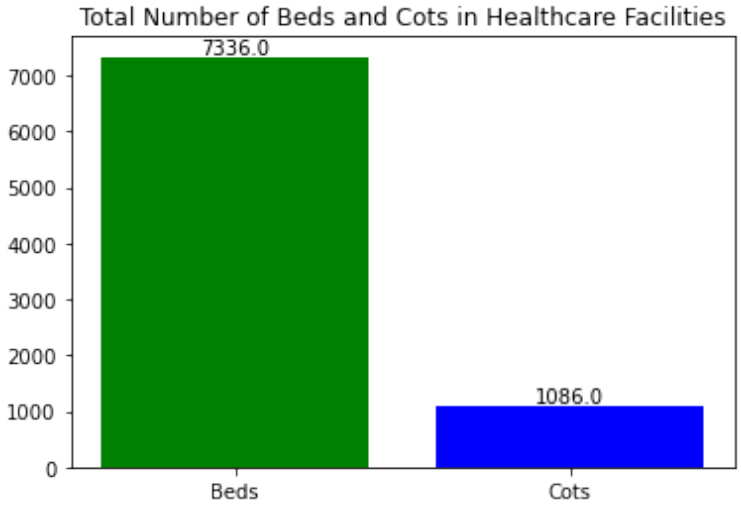
```
## Let's visualise this information
# Define categories and corresponding percentages
categories = ['Open 24 Hours', 'Open Weekends']
percentages = [percentage_open_24_hours, percentage_open_weekends]

# Create the bar chart
plt.figure(figsize=(8, 6))
plt.bar(categories, percentages, color=['blue', 'green'])
plt.xlabel('Facility Status')
plt.ylabel('Percentage of Facilities (%)')
plt.title('Percentage of Healthcare Facilities Open 24 Hours vs Open Weekends')
plt.ylim(0, 100)  # Set y-axis limits to ensure visibility of percentages
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate bars with percentages
for i, percentage in enumerate(percentages):
    plt.text(i, percentage + 1, f'{percentage:.2f}%', ha='center', va='bottom')

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



Many healthcare facilities open weekends(54.78%) more than they do 24 hours(21.13%)

In [26]:
```
## Let's see the number of beds and cots in the healthcare facilities

# Count the total number of beds
total_beds = Nairobi_df['Beds'].sum()

# Count the total number of cots
total_cots = Nairobi_df['Cots'].sum()

# Print the total number of beds and cots
print("Total number of beds in healthcare facilities:", total_beds)
print("Total number of cots in healthcare facilities:", total_cots)

# Plot bar chart for facility count by beds and cots
categories = ['Beds', 'Cots']
totals = [total_beds, total_cots]

plt.figure(figsize=(6, 4))
plt.bar(categories, totals, color=['green','blue'])
plt.title('Total Number of Beds and Cots in Healthcare Facilities')

# Annotate bars with values
for i, total in enumerate(totals):
    plt.text(i, total, str(total), ha='center', va='bottom')
plt.show()
```

```
Total number of beds in healthcare facilities: 7336.0
Total number of cots in healthcare facilities: 1086.0
```



Many facilities have more beds than they do cots. Let's investigate which type of healthcare facilities have beds and cots.

In [27]:
```
## Now lets see the size of various healthcare facilities by the number of beds

# Group the data by 'Type' and calculate the sum of beds and cots for each type
beds_cots_distribution = Nairobi_df.groupby('Type')[['Beds', 'Cots']].sum()
beds_cots_distribution
```

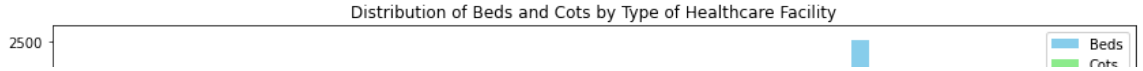
Out[27]:

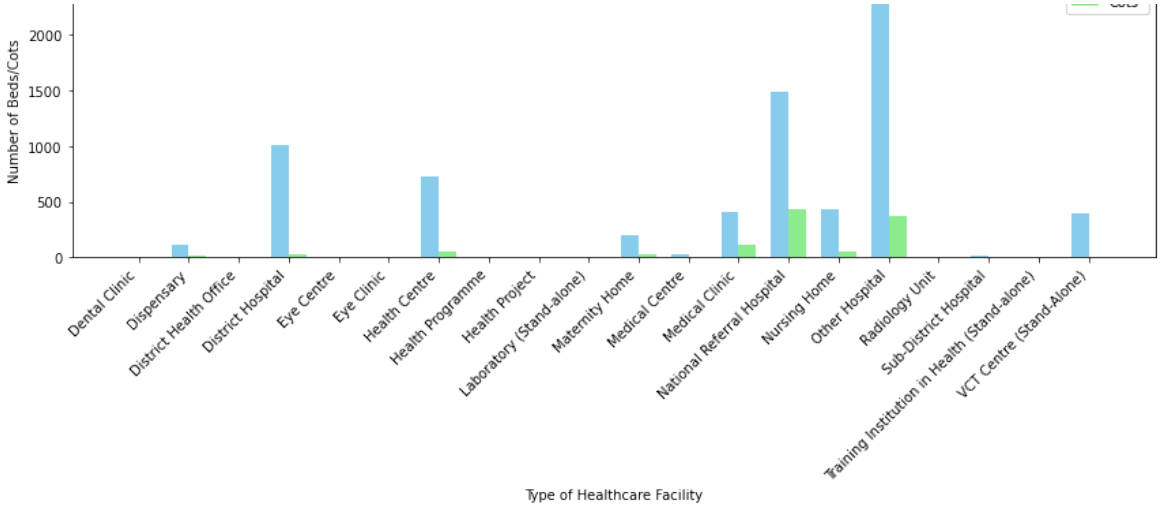
	Beds	Cots

Type		
Dental Clinic	0.0	0.0
Dispensary	116.0	18.0
District Health Office	0.0	0.0
District Hospital	1012.0	22.0
Eye Centre	0.0	0.0
Eye Clinic	0.0	0.0
Health Centre	721.0	56.0
Health Programme	0.0	0.0
Health Project	0.0	0.0
Laboratory (Stand-alone)	0.0	0.0
Maternity Home	205.0	23.0
Medical Centre	22.0	1.0
Medical Clinic	411.0	114.0
National Referral Hospital	1485.0	427.0
Nursing Home	434.0	57.0
Other Hospital	2521.0	367.0
Radiology Unit	0.0	0.0
Sub-District Hospital	15.0	0.0
Training Institution in Health (Stand-alone)	4.0	1.0
VCT Centre (Stand-Alone)	390.0	0.0

In [28]:

```
## Visualising the above information
# Plot the distribution of beds and cots
plt.figure(figsize=(12, 6))
bar_width = 0.35
index = range(len(beds_cots_distribution.index))

plt.bar(index, beds_cots_distribution['Beds'], bar_width, label='Beds', color='
plt.bar([i + bar_width for i in index], beds_cots_distribution['Cots'], bar_wid

plt.xlabel('Type of Healthcare Facility')
plt.ylabel('Number of Beds/Cots')
plt.title('Distribution of Beds and Cots by Type of Healthcare Facility')
plt.xticks([i + bar_width / 2 for i in index], beds_cots_distribution.index, ro
plt.legend()
plt.tight_layout()
plt.show()
```



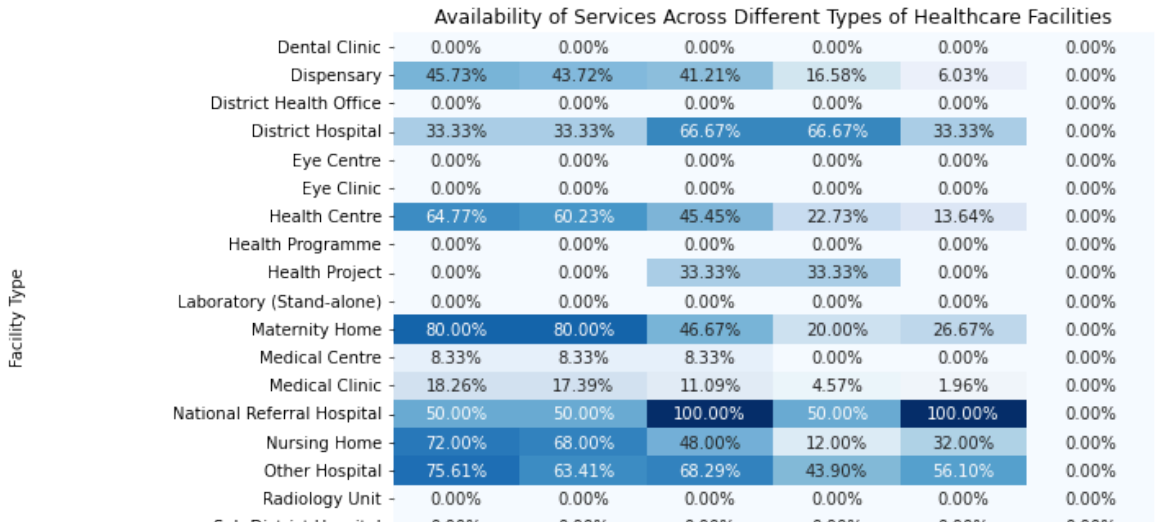


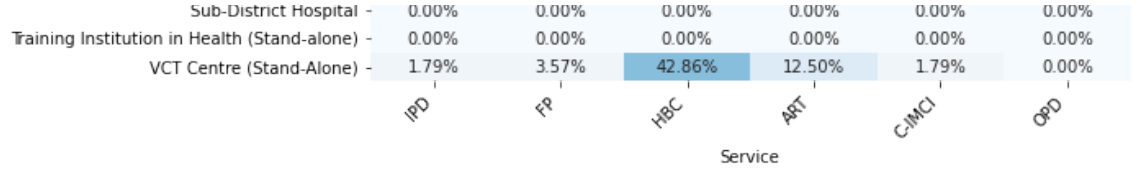
- 'Other Hospital' have the most beds(2521) and National Referral Hospital have the most cots(427)
- Some facilities have no beds nor cots like dental and eye clinics

Note* Beds are typically more permanent fixtures for patients that require extended stays in inpatient care whereas cots are smaller and more portable than beds commonly for temporary accomodations.

In [60]:

```
### Lets investigate the different types of facilities and the services they of

# Group the data by facility type and calculate service availability
service_availability_by_type = Nairobi_df.groupby('Type')[['IPD', 'FP', 'HBC',

# Heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(service_availability_by_type.set_index('Type'), cmap='Blues', annot
plt.xlabel('Service')
plt.ylabel('Facility Type')
plt.title('Availability of Services Across Different Types of Healthcare Facili
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

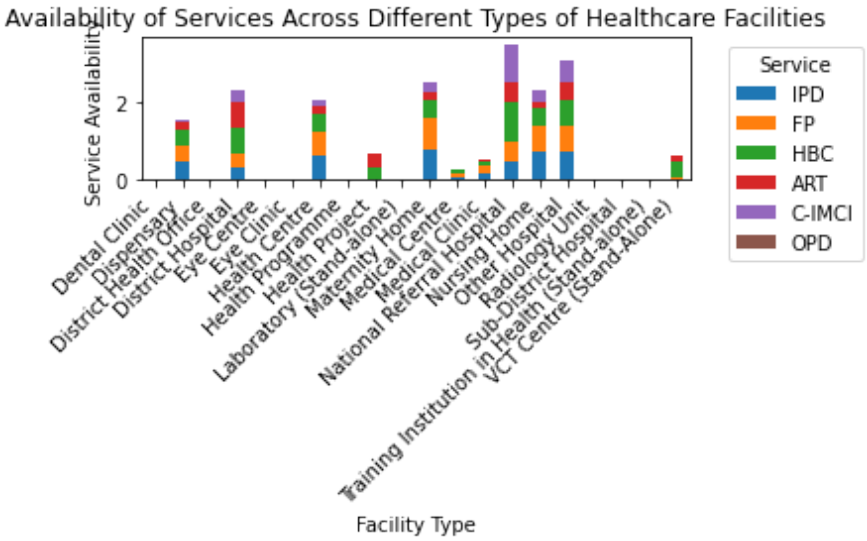




In [59]:

```
# Stacked Bar Chart
plt.figure(figsize=(10, 6))
ax = service_availability_by_type.set_index('Type').plot(kind='bar', stacked=Tr
plt.xlabel('Facility Type')
plt.ylabel('Service Availability')
plt.title('Availability of Services Across Different Types of Healthcare Facili
plt.legend(title='Service', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

```
<Figure size 720x432 with 0 Axes>
```

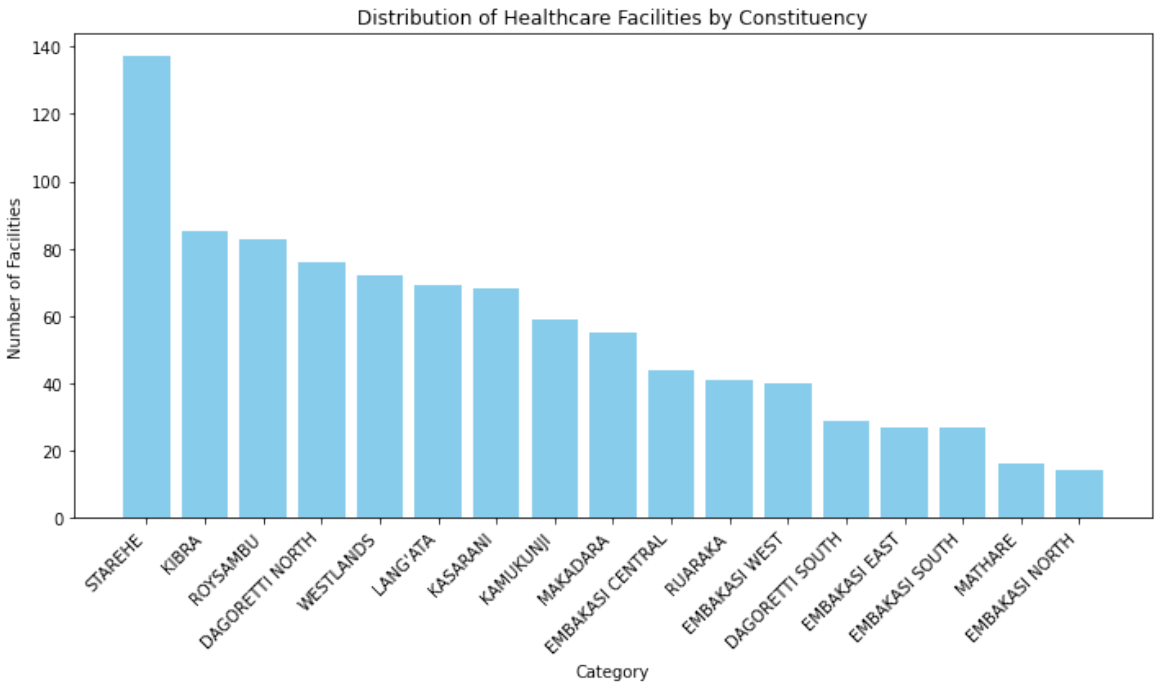


From the above visualisations, we can see that most services are offered by the dispensaries and medical clinics.

In [31]:

```
## Let's investigate the distribution of healthcare facilities according to loc

# Define a function to plot bar chart, pie chart, or histogram
def plot_distribution(data, title, chart_type='bar'):
    plt.figure(figsize=(10, 6))

    if chart_type == 'bar':
        plt.bar(data.index, data.values, color='skyblue')

    plt.xlabel('Category')
    plt.ylabel('Number of Facilities')
    plt.title(title)
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
    plt.show()

# Plot distribution of healthcare facilities by constituency
constituency_distribution = Nairobi_df['Constituency'].value_counts()
```

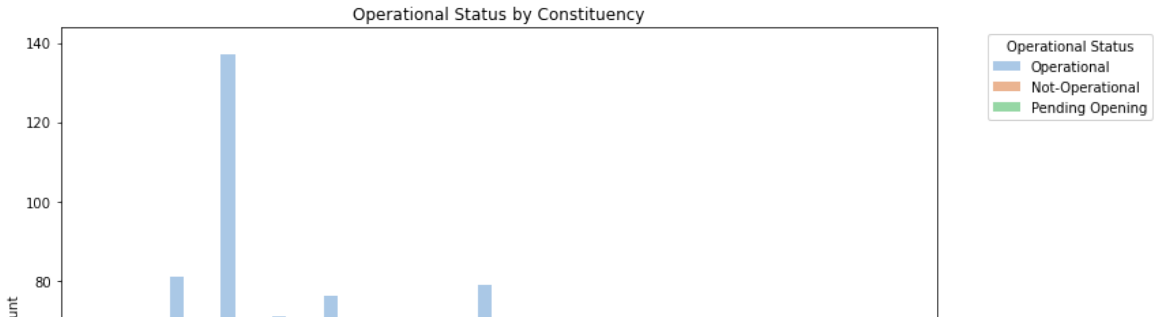
```
plot_distribution(constituency_distribution, 'Distribution of Healthcare Facili
```

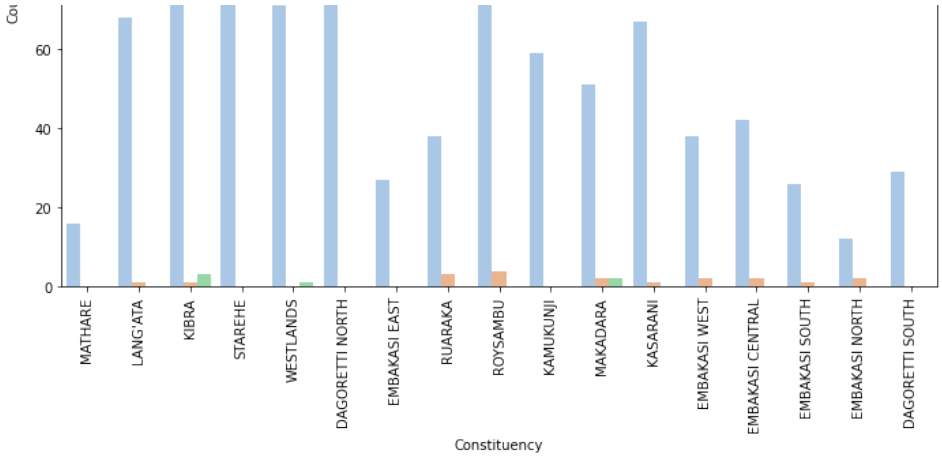


Starehe has the most healthcare facilities

In [32]:

```
### Let's the check the relation of the operational status of a facility and it

# Sample DataFrame (replace this with your actual DataFrame)
data = {
    'Constituency': Nairobi_df['Constituency'].tolist(),
    'Operational Status': Nairobi_df['Operational Status'].tolist()
}

df2 = pd.DataFrame(data)

## Plot grouped bar chart
plt.figure(figsize=(12, 8))
sns.countplot(data=df2, x='Constituency', hue='Operational Status', palette='pa
plt.xlabel('Constituency')
plt.ylabel('Count')
plt.title('Operational Status by Constituency')
plt.legend(title='Operational Status', bbox_to_anchor=(1.05, 1), loc='upper lef
plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
plt.tight_layout()
plt.show()
```

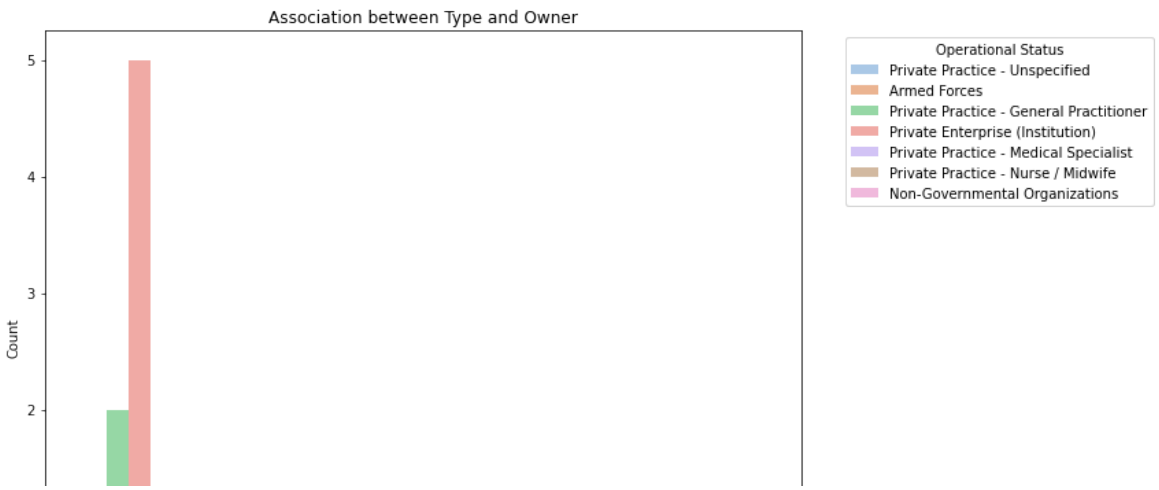


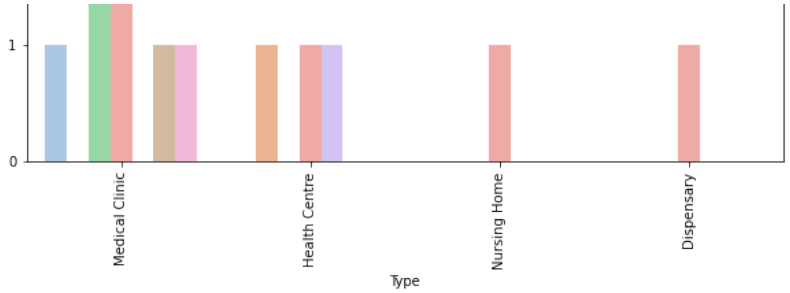


Starehe has the most operational facilities, Royssambu has the most non-operational facilities and Kibra has the most facilities pending opening.

In [33]:

```
### The correlation between the type of facility and the owner

# Sample DataFrame (replace this with your actual DataFrame)
data = {
    'Type': Nairobi_df['Type'][:15].tolist(),
    'Owner': Nairobi_df['Owner'][:15].tolist()
}
df3 = pd.DataFrame(data)
# Count the occurrences of each owner
top_owners= df3['Owner'].value_counts().nlargest(15).index

# Filter the DataFrame to include only the top 10 owners
newdf3 = df3[df3['Owner'].isin(top_owners)]

## Plot grouped bar chart
plt.figure(figsize=(12, 8))
sns.countplot(data=newdf3, x='Type', hue='Owner', palette='pastel')
plt.xlabel('Type')
plt.ylabel('Count')
plt.title('Association between Type and Owner')
plt.legend(title='Operational Status', bbox_to_anchor=(1.05, 1), loc='upper lef
plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
plt.tight_layout()
plt.show()
```



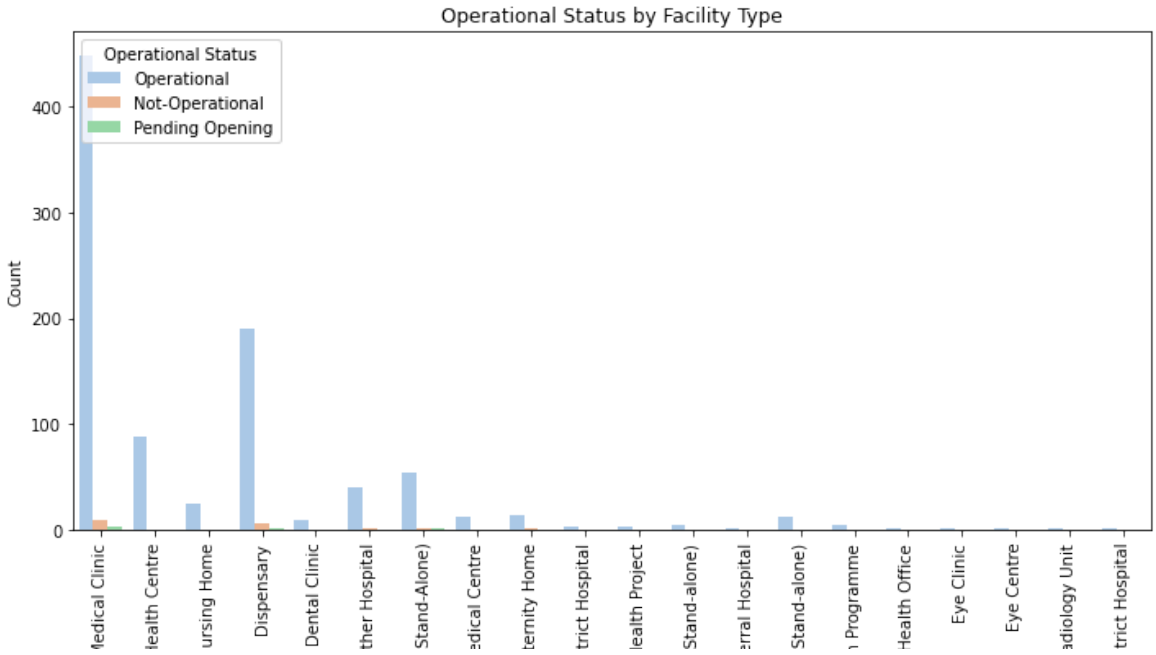


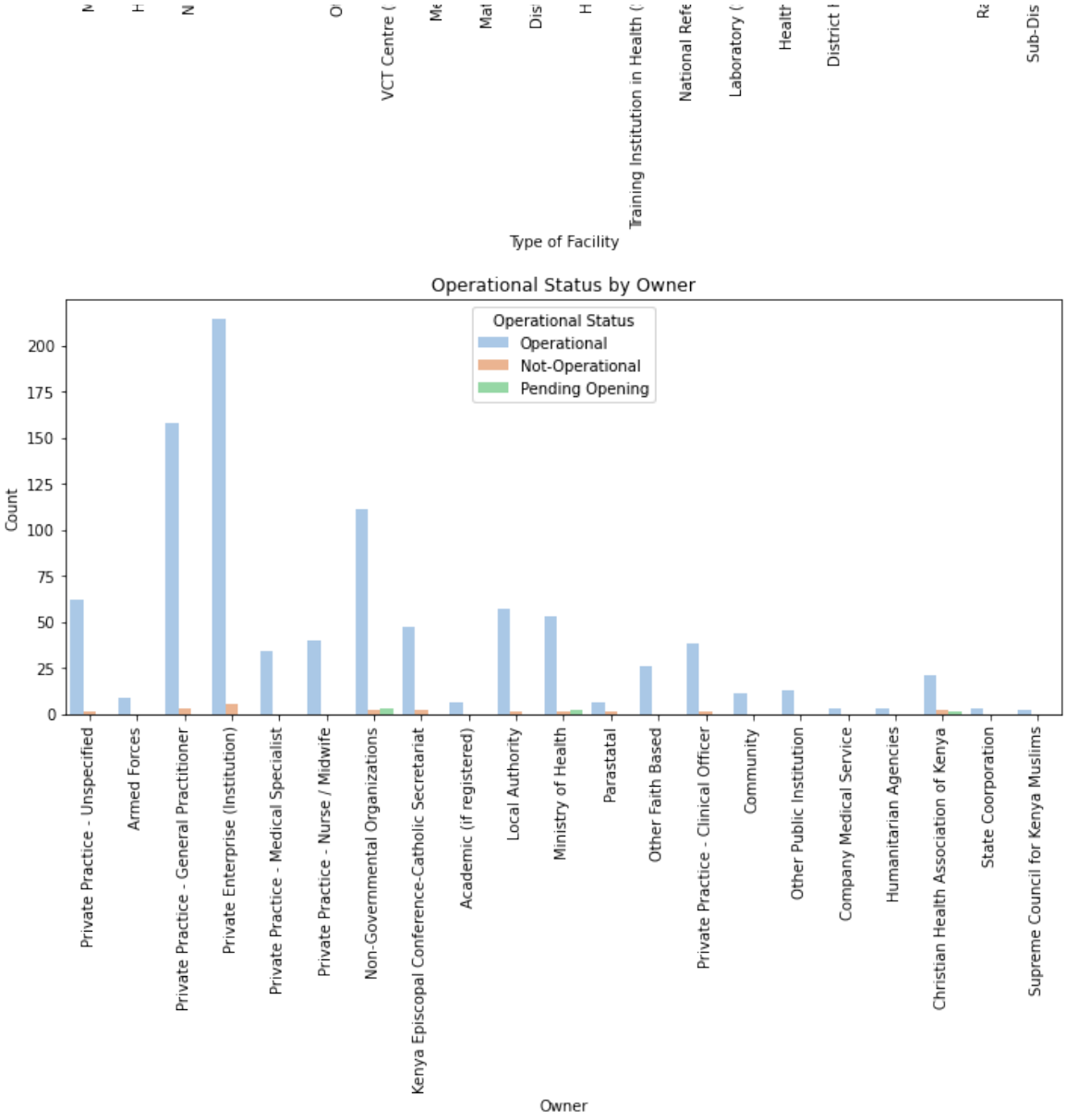
Most of the healthcare facilities in Nairobi are owned by private enterprises.

Some medical clinics are owned by general practitioners

In [34]:

```
### We can also see if different facilites are operational by type and owner

# Plot between Type and Operational Status
plt.figure(figsize=(10, 8))
sns.countplot(data=Nairobi_df, x='Type', hue='Operational Status', palette='pas
plt.xlabel('Type of Facility')
plt.ylabel('Count')
plt.title('Operational Status by Facility Type')
plt.xticks(rotation=90)
plt.legend(title='Operational Status')
plt.tight_layout()
plt.show()

# Plot between Owner and Operational Status
plt.figure(figsize=(10, 8))
sns.countplot(data=Nairobi_df, x='Owner', hue='Operational Status', palette='pa
plt.xlabel('Owner')
plt.ylabel('Count')
plt.title('Operational Status by Owner')
plt.xticks(rotation=90)
plt.legend(title='Operational Status')
plt.tight_layout()
plt.show()
```





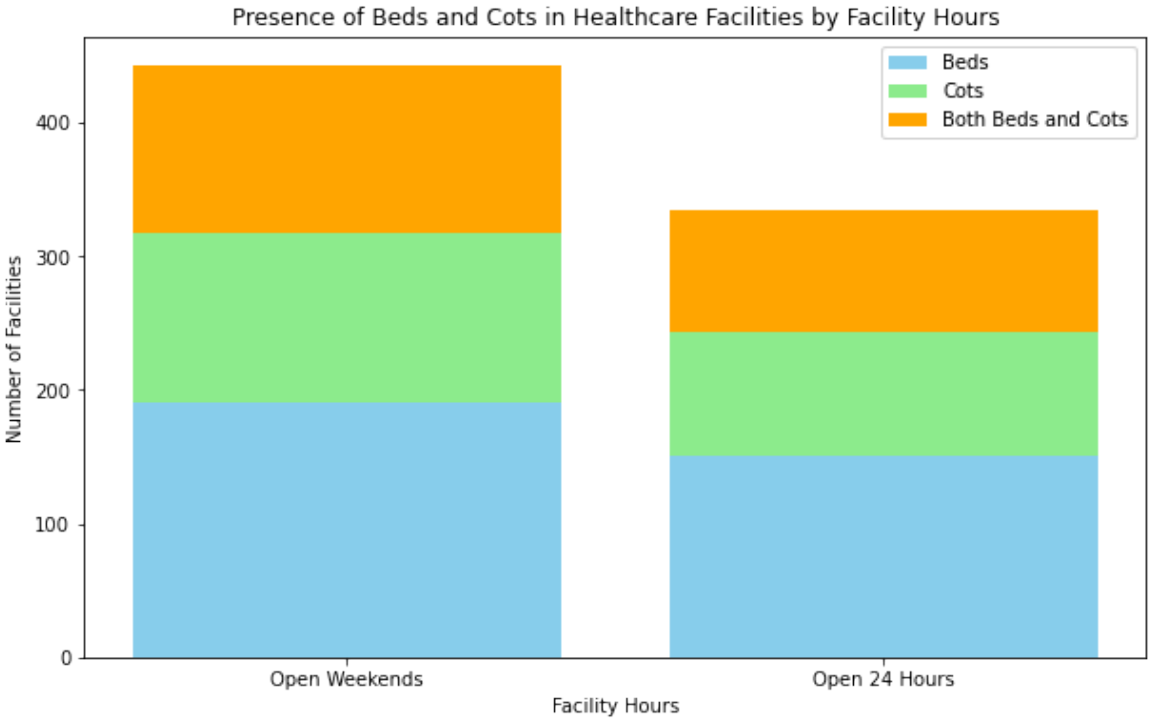
- Medical Centres and Dispensaries have both the most operational and non-operational facilities.
- Private institutions have the most operational and non-operatinal facilities.
- Non-governmental organizations and the Ministry of Health have the highest number of facilities that are pending opening

2.3.3 Multivariate Analysis

This is the analysis of more than 2 variables at the same ime and finding out if they are correlated

In [35]:
```
## Correlation of availability of beds and cots with whether a facility opens o

# Filter data for facilities open on weekends
open_weekends = Nairobi_df[Nairobi_df['Open Weekends'] == 'Y']

# Count facilities with beds and cots open on weekends
open_weekends_with_beds = open_weekends[open_weekends['Beds'] > 0].shape[0]
```

```
open_weekends_with_beds = open_weekends[open_weekends['Beds'] > 0].shape[0]
open_weekends_with_cots = open_weekends[open_weekends['Cots'] > 0].shape[0]
open_weekends_with_both = open_weekends[(open_weekends['Beds'] > 0) & (open_wee

# Filter data for facilities open 24 hours
open_24_hours = Nairobi_df[Nairobi_df['Open 24 Hours'] == 'Y']

# Count facilities with beds and cots open 24 hours
open_24_hours_with_beds = open_24_hours[open_24_hours['Beds'] > 0].shape[0]
open_24_hours_with_cots = open_24_hours[open_24_hours['Cots'] > 0].shape[0]
open_24_hours_with_both = open_24_hours[(open_24_hours['Beds'] > 0) & (open_24_

# Data for the stacked bar chart
categories = ['Open Weekends', 'Open 24 Hours']
beds = [open_weekends_with_beds, open_24_hours_with_beds]
cots = [open_weekends_with_cots, open_24_hours_with_cots]
both = [open_weekends_with_both, open_24_hours_with_both]

# Plotting the stacked bar chart
plt.figure(figsize=(10, 6))
plt.bar(categories, beds, color='skyblue', label='Beds')
plt.bar(categories, cots, bottom=beds, color='lightgreen', label='Cots')
plt.bar(categories, both, bottom=[i+j for i,j in zip(beds, cots)], color='orang

plt.xlabel('Facility Hours')
plt.ylabel('Number of Facilities')
plt.title('Presence of Beds and Cots in Healthcare Facilities by Facility Hours
plt.legend()
plt.show()
```



Many healthcare facilities that open over the weekend have more beds and cots than those that open for 24 hours

In [36]:

```
### Calculate the average number of beds and cots per constituency
average_beds_cots = Nairobi_df.groupby('Constituency')[['Beds', 'Cots']].sum().
```

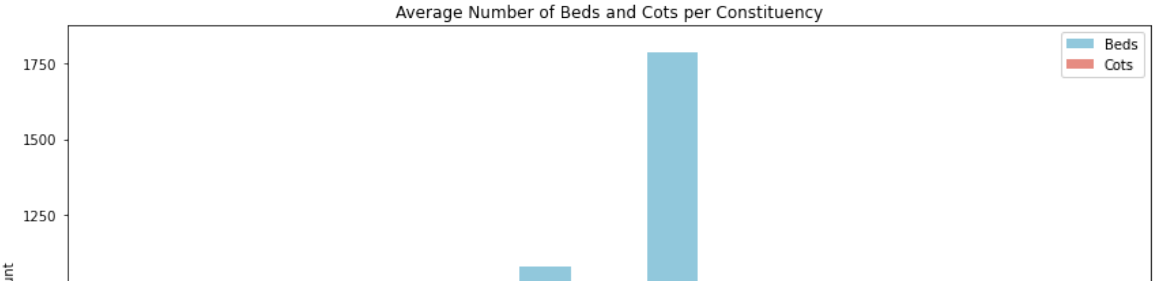
```
average_beds_cots
```

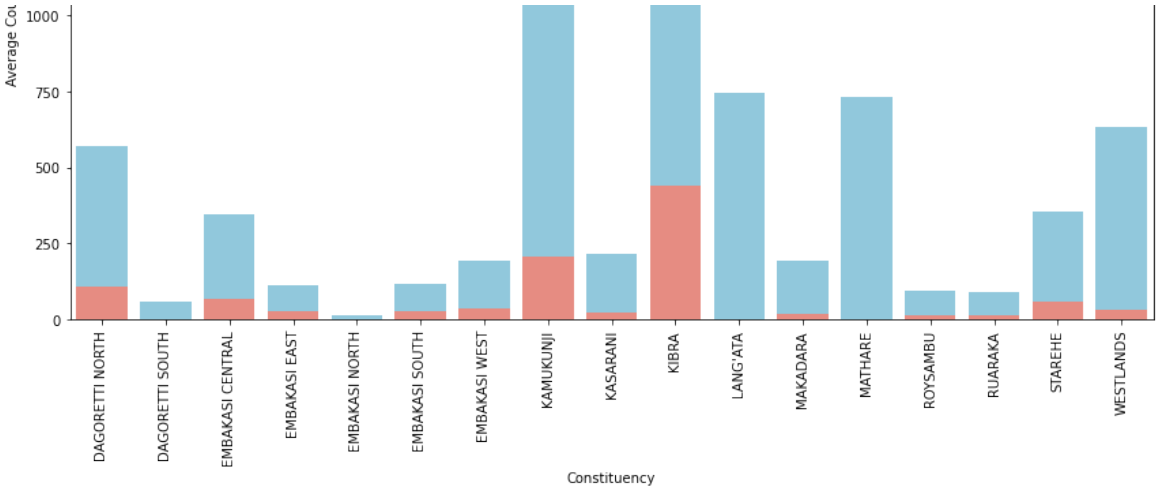
Out[36]:

	Constituency	Beds	Cots
0	DAGORETTI NORTH	569.0	110.0
1	DAGORETTI SOUTH	57.0	2.0
2	EMBAKASI CENTRAL	345.0	68.0
3	EMBAKASI EAST	113.0	29.0
4	EMBAKASI NORTH	12.0	1.0
5	EMBAKASI SOUTH	117.0	28.0
6	EMBAKASI WEST	192.0	36.0
7	KAMUKUNJI	1083.0	206.0
8	KASARANI	217.0	25.0
9	KIBRA	1784.0	441.0
10	LANG'ATA	746.0	0.0
11	MAKADARA	195.0	19.0
12	MATHARE	730.0	0.0
13	ROYSAMBU	96.0	16.0
14	RUARAKA	90.0	15.0
15	STAREHE	357.0	58.0
16	WESTLANDS	633.0	32.0

In [37]:

```
# Plot the average number of beds and cots per constituency
plt.figure(figsize=(12, 8))
sns.barplot(data=average_beds_cots, x='Constituency', y='Beds', color='skyblue'
sns.barplot(data=average_beds_cots, x='Constituency', y='Cots', color='salmon',
plt.xlabel('Constituency')
plt.ylabel('Average Count')
plt.title('Average Number of Beds and Cots per Constituency')
plt.xticks(rotation=90)
plt.legend()
plt.tight_layout()
plt.show()
```





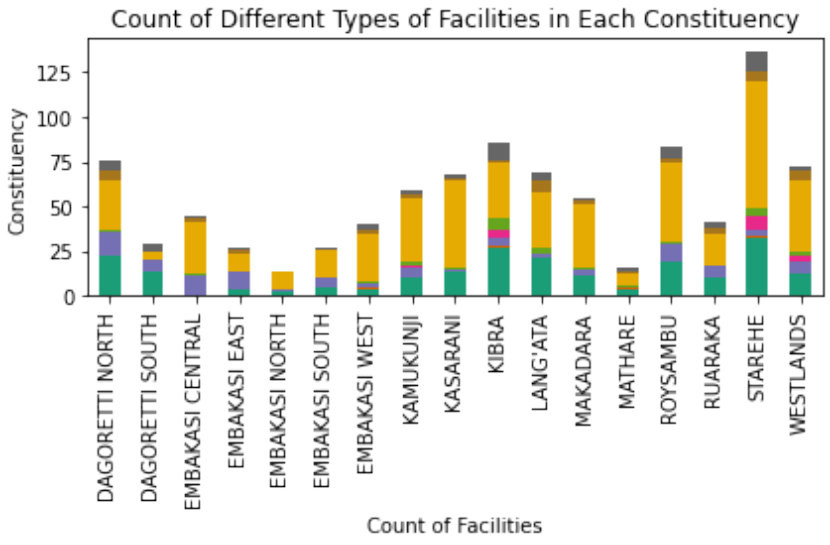
Kamukunji constituency has the most beds(1083) and cots(206.0) whereas Embakasi North has the least beds(12) and cots

Langata and Mathare have no cots at all

In [38]:

```
# Group the data by 'Constituency' and 'Type' and count the number of facilitie
facility_count = Nairobi_df.groupby(['Constituency', 'Type']).size().unstack(fi

# Plot the stacked bar chart
plt.figure(figsize=(12,8 ))
barwidth=1.5
ax = facility_count.plot(kind='bar', stacked=True, colormap='Dark2')
plt.xlabel('Count of Facilities')
plt.ylabel('Constituency')
plt.title('Count of Different Types of Facilities in Each Constituency')
plt.xticks(rotation=90)
plt.legend(title='Type', bbox_to_anchor=(1.05, 1), loc='upper left')
ax.legend().remove()
plt.tight_layout()
plt.show()
```

```
<Figure size 864x576 with 0 Axes>
```



- Every constituency has a medical clinic. Starehe has the most and Mathare has the

Every constituency has a medical clinic, Starehe has the most and Mathare has the least.

- Followed by a dispensary, Kibra has the most whereas Embakasi Central has none.
- Only Starehe(9) and Dagoretti North(1) have a dental clinic.
- The only constituencies that have a laboratories are Kibra(5), Starehe(7) and Westlands(1)
- The only radiology unit is in Starehe
- There are only 2 National Referral Hospitals in Kibra and Dagoretti North
- Many of the healthcare facilities are found in Starehe Constituency
- Embakasi North has the least number of healthcare facilities

*** Let's do an an analysis of the population data

In [40]:
```
Nairobi_pop_df
```

Out[40]:

	county	sub-county	Age	Male	Female	Total
31604	NAIROBI	ALL	Total	2192452	2204376	4396828
31605	NAIROBI	ALL	0	57265	56523	113788
31606	NAIROBI	ALL	1	56019	54601	110620
31607	NAIROBI	ALL	2	52518	51848	104366
31608	NAIROBI	ALL	3	51115	51027	102142
...	...	...	...	...	...	...
33075	NAIROBI	WESTLANDS	98	3	8	11
33076	NAIROBI	WESTLANDS	99	9	14	23
33077	NAIROBI	WESTLANDS	95-99	29	63	92
33078	NAIROBI	WESTLANDS	100+	7	16	23
33079	NAIROBI	WESTLANDS	Not Stated	3	7	10

1476 rows × 6 columns

In [65]:
```
## We want to use the age groups that have already been provided in the dataset

# Regular expression to match age ranges
age_range_pattern = r'^\d+\s*-\s*\d+$'

# Filter rows where 'Age' column matches the age range pattern
age_range_rows = Nairobi_pop_df['Age'].str.match(age_range_pattern)

# Filter the DataFrame to include only rows where 'Age' column represents a ran
age_range_df = Nairobi_pop_df[age_range_rows]

print(age_range_df)


## Let's plot a population distribution chart
```

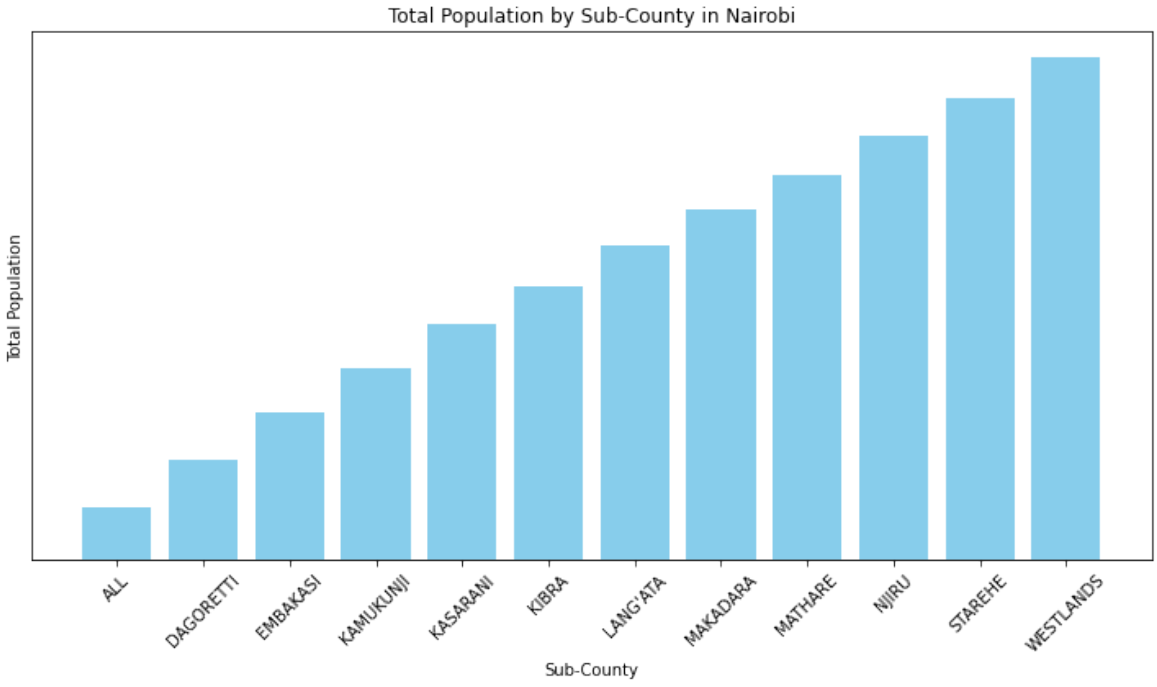
	county	sub-county	Age	Male	Female	Total
31610	NAIROBI	ALL	0 - 4	264099	260888	524987
31616	NAIROBI	ALL	5-9	215230	217482	432712
31622	NAIROBI	ALL	10 -14	185008	193542	378550
31628	NAIROBI	ALL	15-19	159098	192755	351853
31634	NAIROBI	ALL	20-24	249534	313485	563019
...	...	...	...	...	...	...
33053	NAIROBI	WESTLANDS	75-79	914	990	1904
33059	NAIROBI	WESTLANDS	80-84	571	672	1243
33065	NAIROBI	WESTLANDS	85-89	285	369	654
33071	NAIROBI	WESTLANDS	90-94	84	124	208
33077	NAIROBI	WESTLANDS	95-99	29	63	92

[240 rows x 6 columns]

In [64]:

```
## Visualising the distribution population in subcounties in Nairobi
# Plotting
plt.figure(figsize=(10, 6))
plt.bar(Nairobi_pop_df['sub-county'], Nairobi_pop_df['Total'], color='skyblue')
plt.title('Total Population by Sub-County in Nairobi')
plt.xlabel('Sub-County')
plt.ylabel('Total Population')
plt.xticks(rotation=45)
plt.yticks([])
plt.tight_layout()
plt.show()
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_16868\3024629970.py:8: MatplotlibDeprecationWarning: Support for passing numbers through unit converters is deprecated since 3.5 and support will be removed two minor releases later; use Axis.convert_units instead.
  plt.yticks([])
```



Most of Nairobi's population lives in Westlands constituency and the constituency with the least is Dagoretti

the least is Dagoretti

3. Data Report

The following is a summary of the data exploration and analysis;

1. The type of healthcare facilities with the high number is the medical clinics(460), followed by dispensaries(199)
2. Most of the healthcare facilities in Nairobi are owned by private enterprises(219), followed by Private Practice - General Practitioners(161), and the Supreme Council for Kenya Muslims(2)
3. 917 facilities are operational, 19 are not and 6 are pending opening.
4. The services that are offered by most healthcare facilities is Inpatient Care(IPD-297) followed by Family Planning(280). Other services offered are Home-Based Care(250), Anti-retro Treatment(109) and C-IMCI: Community-based Integrated Management of Childhood Illnesses(72)
5. Healthcare facilities that are open 24 hours: 199

- Healthcare facilities that are open on weekends: 516
- Percentage of facilities open 24 hours: 21.13%
- Percentage of facilities open weekends: 54.78%

6. Total number of beds in healthcare facilities: 7336.0 Total number of cots in healthcare facilities: 1086.0
7. 'Other Hospital' have the most beds(2521) and National Referral Hospital have the most cots(427)

- Some facilities have no beds nor cots like dental and eye clinics

8. Most services are offered by the dispensaries and medical clinics
9. Starehe has the most healthcare facilities
10. Starehe has the most operational facilities, Royssambu has the most non-operational facilities and Kibra has the most facilities pending opening.
11. Most of the healthcare facilities in Nairobi are owned by private enterprises.

- Some medical clinics are owned general practitioners

12. Medical Centres and Dispensaries have both the most operational and non-operational facilities.

- Private institutions have the most operational and non-operational facilities.
- Non-governmental organisations and the Ministry of Health have the highest number of facilities that are pending opening

13. Many healthcare facilities that open over the weekend have more beds and cots than those that open for 24 hours
14. Kamukunji constituency has the most beds(1083) and cots(206.0) whereas Embakasi North has the least beds(12) and cots Langata and Mathare have no cots at all

15. Every constituency has a medical clinic, Starehe has the most and Mathare has the least.

- Followed by a dispensary, Kibra has the most whereas Embakasi Central has none.
- Only Starehe(9) and Dagoretti North(1) have a dental clinic.
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