

# fp-demand-optimization

July 25, 2025

## 1 Predicting Family Planning Demand and Optimizing Service Delivery in Kenya

### 1.1 Project Overview

This project aims to enhance family planning (FP) service delivery efficiency by leveraging data-driven approaches, specifically machine learning (ML) using the CRISP-DM methodology. The goal is to improve maternal and child health outcomes, reduce unmet need for family planning, and contribute to achieving national and global development goals related to reproductive health.

### 1.2 Problem Statement

Kenya faces significant strides in increasing access to family planning services, yet a substantial unmet need for family planning remains. According to the 2022 Kenya Demographic and Health Survey (KDHS), the total unmet need for family planning is 15%, with 10% for spacing and 5% for limiting births. This indicates that a significant portion of the population desires to space or limit births but is not using any contraceptive method. Traditional methods often show imbalances, with a heavy reliance on short-acting methods, leading to unstable uptake of long-acting reversible contraceptives (LARCs) and permanent methods. This disparity can lead to higher discontinuation rates and continued unmet need. Supply chain inefficiencies, commodity stock-outs, inadequate healthcare worker training, and uneven distribution of resources exacerbate these issues, hindering effective service delivery.

### 1.3 Stakeholders

- **Government of Kenya:** Ministry of Health (MoH), especially the National Family Planning Coordinated Implementation Plan (NFPICIP) and Kenya Health Information System (KHIS) initiatives.
- **Policymakers and Donors:** Need evidence-based advocacy for resource mobilization and investment.
- **Healthcare Providers:** Frontline health workers providing FP services.
- **Women of Reproductive Age:** Direct beneficiaries of improved FP services.
- **Local Communities:** Impacted by and involved in FP service delivery.

### 1.4 Key Statistics

- **Total Unmet Need for Family Planning (2022 KDHS):** 15%
  - **Unmet Need for Spacing:** 10%
  - **Unmet Need for Limiting Births:** 5%

- **Married Women Aged 15-49 Rising to 57% in 2022 (DRS 2022):** Modern contraceptive prevalence rate (mCPR).
- **Number of new clients for FP method band and the continuation rate:** Key data points for predicting future demand.

## 1.5 Key Analytics Questions

- How many new clients are expected for injectables in a County next quarter?
- What is the projected demand for different family planning methods (injectables, pills, condoms, implants, IUD, sterilization) at various geographical (e.g., county) and temporal (e.g., quarterly, annual) granularities?
- How can we optimize resource allocation (commodities, equipment, staffing) to meet projected demand and minimize wastage?
- How can predictive analytics identify potential stock-outs or oversupply of specific FP commodities in different locations?
- Which regions or demographics are most underserved in terms of family planning access and uptake?

## 1.6 Objectives

- **Quantitatively forecast the demand for specific family planning methods:** This includes predicting the continuation rates of users for each method at defined geographical and temporal scales.
- **Enable proactive resource allocation:** This involves optimizing the distribution of commodities, equipment, and staffing to reduce stock-outs, minimize wastage, and improve targeted interventions.
- **Improve method continuation:** By understanding demand and improving service delivery, the project aims to reduce discontinuation rates and increase sustained use of FP methods.
- **Provide evidence-based insights:** Support policymakers and donors in making informed decisions regarding resource mobilization and investment in family planning.

## 1.7 Metrics of Importance to Focus On

- **Accuracy of Demand Forecasts:** Measured by comparing predicted demand with actual uptake for various FP methods at different geographical and temporal levels (e.g., Mean Absolute Error, Root Mean Squared Error).
- **Commodity Stock-out Rates:** Reduction in the number or duration of stock-outs for essential family planning commodities.
- **Resource Utilization Efficiency:** Metrics related to optimal allocation and reduced wastage of commodities, equipment, and human resources.
- **Method Continuation Rates:** Increase in the percentage of users who continue using a specific family planning method over a defined period (e.g., 12-month continuation rate).
- **Unmet Need for Family Planning:** Contribution to the reduction of the national unmet need for family planning.
- **Client Satisfaction:** Indirectly improved through better access and availability of preferred methods.
- **Healthcare Worker Productivity:** Optimized allocation of staff to meet demand efficiently.

## 2 Preliminaries

### 2.1 Importing Python Libraries

```
[198]: #Import necessary libraries for data manipulation, visualization, and machine_
      ↪learning
# Data handling and manipulation
import pandas as pd          # For dataframes and data manipulation
import numpy as np           # For numerical operations and arrays

# Visualization libraries
import matplotlib.pyplot as plt  # For basic plotting
import seaborn as sns           # For advanced statistical visualizations

# Suppress warning messages
import warnings                # To filter out warnings during execution

# Model selection and evaluation
from sklearn.model_selection import train_test_split, cross_val_score, ↪
      ↪TimeSeriesSplit
# train_test_split: splits data into training and test sets
# cross_val_score: performs cross-validation
# TimeSeriesSplit: cross-validation for time series data such as this FP data
from sklearn.model_selection import GridSearchCV

# Data preprocessing
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder
# StandardScaler/MinMaxScaler: scale numerical features
# OneHotEncoder: encode categorical variables

# Metrics for model evaluation
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
# MAE, MSE, R2: performance metrics for regression models

# Combine preprocessing steps
from sklearn.compose import ColumnTransformer # Apply different preprocessing_
      ↪to columns

# Build machine learning workflows
from sklearn.pipeline import Pipeline        # Chain preprocessing and_
      ↪modeling steps

# Handle missing data
from sklearn.impute import SimpleImputer     # Fill missing values

# Regression models
```

```

from sklearn.linear_model import LinearRegression, Ridge #
    ↳ Linear regression model
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.multioutput import MultiOutputRegressor
from xgboost import XGBRegressor

# RandomForestRegressor: ensemble method using decision trees
# GradientBoostingRegressor: boosting method for better accuracy

```

## 2.2 Data Loading

```

[2]: # from google.colab import drive
# drive.mount('/content/drive') # Mount Google Drive

# base_path = "/content/drive/MyDrive/data/"

# # File paths
# population_data_path = base_path + "ke_fp_population_data.csv"
# service_data_path = base_path + "ke_fp_service_data.csv"
# benchmarks_data_path = base_path + "ke_fp_benchmarks_data.csv"
# commodity_data_path = base_path + "ke_fp_commodity_data.csv"

# # Attempt to read with 'latin1' encoding
# df_population = pd.read_csv(population_data_path, encoding='latin1')
# df_service = pd.read_csv(service_data_path, encoding='latin1')
# df_benchmarks = pd.read_csv(benchmarks_data_path, encoding='latin1')
# df_commodity = pd.read_csv(commodity_data_path, encoding='latin1')

```

```

[3]: # Data loading

try:
    # Define paths
    data_dir = "data/"
    benchmarks_dir = "data/benchmarks/"

    population_data_path = f"{data_dir}ke_fp_population_data.csv"
    service_data_path = f"{data_dir}ke_fp_service_data.csv"
    commodity_data_path = f"{data_dir}ke_fp_commodity_data.csv"

    benchmarks_core_health_workforce_data_path =
    ↳ f"{benchmarks_dir}ke_fp_benchmarks_core_health_workforce.csv"
    benchmarks_demand_satisfied_data_path =
    ↳ f"{benchmarks_dir}ke_fp_benchmarks_Demand_Satisfied.csv"
    benchmarks_mCPR_data_path = f"{benchmarks_dir}ke_fp_benchmarks_mCPR.csv"

```

```

    benchmarks_teen_pregnancy_data_path =
↳f"{benchmarks_dir}ke_fp_benchmarks_Teenage_Pregnancy_rate.csv"
    benchmarks_unmet_need_data_path =
↳f"{benchmarks_dir}ke_fp_benchmarks_Total_Unmet_Need_MW.csv"

    # Load CSVs with fallback encoding
    df_population = pd.read_csv(population_data_path, encoding='latin1')
    df_service = pd.read_csv(service_data_path, encoding='latin1')
    df_commodity = pd.read_csv(commodity_data_path, encoding='latin1')

    # Load benchmark-specific CSVs
    df_core_health_workforce = pd.
↳read_csv(benchmarks_core_health_workforce_data_path, encoding='latin1')
    df_demand_satisfied = pd.read_csv(benchmarks_demand_satisfied_data_path,
↳encoding='latin1')
    df_mcpr = pd.read_csv(benchmarks_mCPR_data_path, encoding='latin1')
    df_teenage_pregnancy = pd.read_csv(benchmarks_teen_pregnancy_data_path,
↳encoding='latin1')
    df_unmet_need = pd.read_csv(benchmarks_unmet_need_data_path,
↳encoding='latin1')

    # Success logs
    print("Datasets loaded successfully:")
    print(f"{population_data_path} shape: {df_population.shape}")
    print(f"{service_data_path} shape: {df_service.shape}")
    print(f"{commodity_data_path} shape: {df_commodity.shape}")
    print(f"{benchmarks_core_health_workforce_data_path} shape:
↳{df_core_health_workforce.shape}")
    print(f"{benchmarks_demand_satisfied_data_path} shape: {df_demand_satisfied.
↳shape}")
    print(f"{benchmarks_mCPR_data_path} shape: {df_mcpr.shape}")
    print(f"{benchmarks_teen_pregnancy_data_path} shape: {df_teenage_pregnancy.
↳shape}")
    print(f"{benchmarks_unmet_need_data_path} shape: {df_unmet_need.shape}")

except FileNotFoundError as e:
    print(" Error: One or more CSV files were not found.")
    print(" Please ensure all expected files are in their respective folders.")
    print(e)
except Exception as e:
    print(" An unexpected error occurred while loading the datasets:")
    print(e)

```

Datasets loaded successfully:  
data/ke\_fp\_population\_data.csv shape: (517, 19)  
data/ke\_fp\_service\_data.csv shape: (6204, 60)  
data/ke\_fp\_commodity\_data.csv shape: (2480, 50)

```
data/benchmarks/ke_fp_benchmarks_core_health_workforce.csv shape: (47, 8)
data/benchmarks/ke_fp_benchmarks_Demand_Satisfied.csv shape: (47, 8)
data/benchmarks/ke_fp_benchmarks_mCPR.csv shape: (47, 8)
data/benchmarks/ke_fp_benchmarks_Teenage_Pregnancy_rate.csv shape: (47, 8)
data/benchmarks/ke_fp_benchmarks_Total_Unmet_Need_MW.csv shape: (47, 8)
```

## 3 1. Data Understanding

### 3.1 a) Data Cleaning

This involved; \* Standardization of the column names \* Renaming the columns \* Dropping empty and unwanted columns \* Handling missing values, duplicates and outliers

#### 3.1.1 1. ke\_fp\_service\_data.csv

```
[4]: # Make a copy of the data
df_service1=df_service.copy()
```

```
[5]: # from google.colab import drive
# drive.mount('/content/drive')
```

```
[6]: # Preview the data
df_service1.head()
```

```
[6]:
```

	periodid	periodname	periodcode	perioddescription	orgunitlevel1	\
0	201404	April 2014	201404		NaN	Kenya
1	201404	April 2014	201404		NaN	Kenya
2	201404	April 2014	201404		NaN	Kenya
3	201404	April 2014	201404		NaN	Kenya
4	201404	April 2014	201404		NaN	Kenya

	orgunitlevel2	organisationunitid	organisationunitname	\
0	Turkana County	kphDeKC1Fch	Turkana County	
1	Nandi County	t0J75eHKxz5	Nandi County	
2	West Pokot County	XWALbfAPa6n	West Pokot County	
3	Bomet County	HMNARUV2CW4	Bomet County	
4	Nairobi County	jkG3zaihds	Nairobi County	

	organisationunitcode	organisationunitdescription	...	\
0	KE_County_23		NaN	...
1	KE_County_29		NaN	...
2	KE_County_24		NaN	...
3	KE_County_36		NaN	...
4	KE_County_47		NaN	...

	MOH 711 Rev 2020_Post parturm FP 4weeks to 6weeks Re-visits	\
0		NaN

1	NaN
2	NaN
3	NaN
4	NaN

MOH 711 Rev 2020_Post parturm FP within 48 Hours New clients \	
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

MOH 711 Rev 2020_Post parturm FP within 48 Hours Re-visits \	
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

MOH 711 Rev 2020_Voluntary Surgical Contraception Vasectomy Ist Time Insertion \	
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

MOH 711 Rev 2020_Voluntary Surgical Contraception Vasectomy Re-insertion \	
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

MOH 711 Rev 2020_Voluntary surgical contraception BTL Ist Time Insertion \	
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

MOH 711 Rev 2020_Voluntary surgical contraception BTL Re-insertion \	
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

	Population Growth Rate	Total Population \
0	3.16	999367.0
1	3.02	938866.0
2	3.10	597313.0
3	1568.96	834381.7
4	4.02	3894186.0

	Women of childbearing age (15â 49yrs)
0	225176.0
1	223505.0
2	144549.0
3	237820.0
4	981191.0

[5 rows x 60 columns]

```
[7]: # Explore the data
df_service1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 6204 entries, 0 to 6203
```

```
Data columns (total 60 columns):
```

```
#    Column
```

```
Non-Null Count  Dtype
```

```
---  ---
```

```
-----  ---
```

```

0    periodid
6204 non-null    int64
1    periodname
6204 non-null    object
2    periodcode
6204 non-null    int64
3    perioddescription
0 non-null       float64
4    orgunitlevel1
6204 non-null    object
5    orgunitlevel2
6204 non-null    object
6    organisationunitid
6204 non-null    object
7    organisationunitname
6204 non-null    object
8    organisationunitcode
6204 non-null    object
9    organisationunitdescription
0 non-null       float64
```



10 Estimated Number of Pregnant Women  
 6192 non-null float64  
 11 FP Attendance New clients  
 6204 non-null float64  
 12 FP Attendance Re-visits  
 6204 non-null float64  
 13 MOH 711 Adolescent 10-14 yrs Receiving FP Services New clients  
 4095 non-null float64  
 14 MOH 711 Adolescent 10-14 yrs Receiving FP Services Re-visits  
 3327 non-null float64  
 15 MOH 711 Adolescent 15-19 Yrs Receiving FP Services New clients  
 4980 non-null float64  
 16 MOH 711 Adolescent 15-19 Yrs Receiving FP Services Re-visits  
 4956 non-null float64  
 17 MOH 711 Adolescent 20-24 Yrs Receiving FP Services New clients  
 4972 non-null float64  
 18 MOH 711 Adolescent 20-24 Yrs Receiving FP Services Re-visits  
 4964 non-null float64  
 19 MOH 711 Client receiving Male condoms New clients  
 6204 non-null int64  
 20 MOH 711 Client receiving Male condoms Re-visits  
 6004 non-null float64  
 21 MOH 711 Clients Counselling Natural Family Planning New clients  
 5459 non-null float64  
 22 MOH 711 Clients Counselling Natural Family Planning Re-visits  
 3309 non-null float64  
 23 MOH 711 Clients receiving Female Condoms New clients  
 4141 non-null float64  
 24 MOH 711 Clients receiving Female Condoms Re-visits  
 2826 non-null float64  
 25 MOH 711 Emergency contraceptive pill New clients  
 4837 non-null float64  
 26 MOH 711 Emergency contraceptive pill Re-visits  
 3402 non-null float64  
 27 MOH 711 Pills Combined oral contraceptive New clients  
 6201 non-null float64  
 28 MOH 711 Pills Combined oral contraceptive Re-visits  
 6194 non-null float64  
 29 MOH 711 Pills progestin only New clients  
 6193 non-null float64  
 30 MOH 711 Pills progestin only Re-visits  
 6165 non-null float64  
 31 MOH 711 Rev 2020\_Adults 25+ receiving FP Services New clients  
 2415 non-null float64  
 32 MOH 711 Rev 2020\_Adults 25+ receiving FP Services Re-visits  
 2408 non-null float64  
 33 MOH 711 Rev 2020\_Clients given cycle beads New clients  
 1188 non-null float64

34 MOH 711 Rev 2020\_Clients given cycle beads Re-visits  
 84 non-null float64  
 35 MOH 711 Rev 2020\_Clients receiving post abortion FP New clients  
 2007 non-null float64  
 36 MOH 711 Rev 2020\_Clients receiving post abortion FP Re-visits  
 425 non-null float64  
 37 MOH 711 Rev 2020\_FP Injections DMPA- IM New clients  
 2465 non-null float64  
 38 MOH 711 Rev 2020\_FP Injections DMPA- IM Re-visits  
 2469 non-null float64  
 39 MOH 711 Rev 2020\_FP Injections DMPA- SC New clients  
 2133 non-null float64  
 40 MOH 711 Rev 2020\_FP Injections DMPA- SC Re-visits  
 2108 non-null float64  
 41 MOH 711 Rev 2020\_IUCD Insertion Hormonal Ist Time Insertion  
 2015 non-null float64  
 42 MOH 711 Rev 2020\_IUCD Insertion Hormonal Re-insertion  
 1561 non-null float64  
 43 MOH 711 Rev 2020\_IUCD Insertion Non Hormonal Ist Time Insertion  
 2332 non-null float64  
 44 MOH 711 Rev 2020\_IUCD Insertion Non Hormonal Re-insertion  
 2094 non-null float64  
 45 MOH 711 Rev 2020\_Implants insertion 1 Rod Ist Time Insertion  
 2438 non-null float64  
 46 MOH 711 Rev 2020\_Implants insertion 1 Rod Re-insertion  
 2389 non-null float64  
 47 MOH 711 Rev 2020\_Implants insertion 2 Rod Ist Time Insertion  
 2434 non-null float64  
 48 MOH 711 Rev 2020\_Implants insertion 2 Rod Re-insertion  
 2402 non-null float64  
 49 MOH 711 Rev 2020\_Post parturm FP 4weeks to 6weeks New clients  
 2350 non-null float64  
 50 MOH 711 Rev 2020\_Post parturm FP 4weeks to 6weeks Re-visits  
 1428 non-null float64  
 51 MOH 711 Rev 2020\_Post parturm FP within 48 Hours New clients  
 2208 non-null float64  
 52 MOH 711 Rev 2020\_Post parturm FP within 48 Hours Re-visits  
 1199 non-null float64  
 53 MOH 711 Rev 2020\_Voluntary Surgical Contraception Vasectomy Ist Time  
 Insertion 300 non-null float64  
 54 MOH 711 Rev 2020\_Voluntary Surgical Contraception Vasectomy Re-insertion  
 5 non-null float64  
 55 MOH 711 Rev 2020\_Voluntary surgical contraception BTL Ist Time Insertion  
 1585 non-null float64  
 56 MOH 711 Rev 2020\_Voluntary surgical contraception BTL Re-insertion  
 32 non-null float64  
 57 Population Growth Rate  
 5352 non-null float64

```

58 Total Population
6204 non-null    float64
59 Women of childbearing age (15â 49yrs)
6204 non-null    float64
dtypes: float64(51), int64(3), object(6)
memory usage: 2.8+ MB

```

[8]: *# Standardize the column names*

```

def standardize_col_labels(df):
    def clean_column(col):
        # Remove redundant prefixes
        col = col.replace('MOH 711 Rev ', '')
        col = col.replace('MOH 711 ', '')

        # Formatting
        col = col.strip().lower()           # Convert to lowercase
        col = col.replace(' ', '_')         # Replace spaces with underscores
        col = col.replace('-', '_')         # Replace hyphen with underscores
        col = col.replace('â€', '_')
        col = col.replace('â ', '_')
        return col

    df.columns = [clean_column(col) for col in df.columns]
    return df

df_service1 = standardize_col_labels(df_service1)
df_service1.columns

```

[8]: Index(['periodid', 'periodname', 'periodcode', 'perioddescription',  
'orgunitlevel1', 'orgunitlevel2', 'organisationunitid',  
'organisationunitname', 'organisationunitcode',  
'organisationunitdescription', 'estimated\_number\_of\_pregnant\_women',  
'fp\_attendance\_new\_clients', 'fp\_attendance\_re\_visits',  
'adolescent\_10\_14\_yrs\_receiving\_fp\_services\_new\_clients',  
'adolescent\_10\_14\_yrs\_receiving\_fp\_services\_re\_visits',  
'adolescent\_15\_19\_yrs\_receiving\_fp\_services\_new\_clients',  
'adolescent\_15\_19\_yrs\_receiving\_fp\_services\_re\_visits',  
'adolescent\_20\_24\_yrs\_receiving\_fp\_services\_new\_clients',  
'adolescent\_20\_24\_yrs\_receiving\_fp\_services\_re\_visits',  
'client\_receiving\_male\_condoms\_new\_clients',  
'client\_receiving\_male\_condoms\_re\_visits',  
'clients\_counselled\_natural\_family\_planning\_new\_clients',  
'clients\_counselled\_natural\_family\_planning\_re\_visits',  
'clients\_receiving\_female\_condoms\_new\_clients',  
'clients\_receiving\_female\_condoms\_re\_visits',  
'emergency\_contraceptive\_pill\_new\_clients',

```

'emergency_contraceptive_pill_re_visits',
'pills_combined_oral_contraceptive_new_clients',
'pills_combined_oral_contraceptive_re_visits',
'pills_progestin_only_new_clients', 'pills_progestin_only_re_visits',
'2020_adults_25+_receiving_fp_services_new_clients',
'2020_adults_25+_receiving_fp_services_re_visits',
'2020_clients_given_cycle_beads_new_clients',
'2020_clients_given_cycle_beads_re_visits',
'2020_clients_receiving_post_abortion_fp_new_clients',
'2020_clients_receiving_post_abortion_fp_re_visits',
'2020_fp_injections_dmpa_im_new_clients',
'2020_fp_injections_dmpa_im_re_visits',
'2020_fp_injections_dmpa_sc_new_clients',
'2020_fp_injections_dmpa_sc_re_visits',
'2020_iucd_insertion_hormonal_ist_time_insertion',
'2020_iucd_insertion_hormonal_re_insertion',
'2020_iucd_insertion_non_hormonal_ist_time_insertion',
'2020_iucd_insertion_non_hormonal_re_insertion',
'2020_implants_insertion_1_rod_ist_time_insertion',
'2020_implants_insertion_1_rod_re_insertion',
'2020_implants_insertion_2_rod_ist_time_insertion',
'2020_implants_insertion_2_rod_re_insertion',
'2020_post_parturm_fp_4weeks_to_6weeks_new_clients',
'2020_post_parturm_fp_4weeks_to_6weeks_re_visits',
'2020_post_parturm_fp_within_48_hours_new_clients',
'2020_post_parturm_fp_within_48_hours_re_visits',
'2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion',
'2020_voluntary_surgical_contraception_vasectomy_re_insertion',
'2020_voluntary_surgical_contraception_btl_ist_time_insertion',
'2020_voluntary_surgical_contraception_btl_re_insertion',
'population_growth_rate', 'total_population',
'women_of_childbearing_age_(15_49yrs)'],
dtype='object')

```

[9]: *# Rename column names*

```

name_map = {
    'periodcode': 'year_month',
    'orgunitlevel1': 'country',
    'orgunitlevel2': 'county',
    'organisationunitid': 'uid',
    'organisationunitcode': 'county_code',
    'county_cou': 'county_code',
    'dataname': 'population_indicator'
}
df_service1 = df_service1.rename(columns=name_map)
df_service1

```

```

[9]:      periodid      periodname  year_month  perioddescription  country  \
0      201404      April 2014      201404      NaN      Kenya
1      201404      April 2014      201404      NaN      Kenya
2      201404      April 2014      201404      NaN      Kenya
3      201404      April 2014      201404      NaN      Kenya
4      201404      April 2014      201404      NaN      Kenya
...      ...      ...      ...      ...      ...
6199    202409    September 2024      202409      NaN      Kenya
6200    202409    September 2024      202409      NaN      Kenya
6201    202409    September 2024      202409      NaN      Kenya
6202    202409    September 2024      202409      NaN      Kenya
6203    202409    September 2024      202409      NaN      Kenya

      county      uid  organisationunitname  county_code  \
0      Turkana County  kphDeKC1fCh      Turkana County  KE_County_23
1      Nandi County  t0J75eHKxz5      Nandi County  KE_County_29
2      West Pokot County  XWALbfAPa6n      West Pokot County  KE_County_24
3      Bomet County  HMNARUV2CW4      Bomet County  KE_County_36
4      Nairobi County  jkG3zaihdsS      Nairobi County  KE_County_47
...      ...      ...      ...      ...
6199      Isiolo County  bz0fj0iwfDH      Isiolo County  KE_County_11
6200    Trans Nzoia County  mThvosEflAU      Trans Nzoia County  KE_County_26
6201      Nakuru County  ob6SxuRcqU4      Nakuru County  KE_County_32
6202    Tharaka Nithi County  T4urHM47nlm      Tharaka Nithi County  KE_County_13
6203      Nyeri County  ptWVfaCIdVx      Nyeri County  KE_County_19

      organisationunitdescription  ...  \
0      NaN  ...
1      NaN  ...
2      NaN  ...
3      NaN  ...
4      NaN  ...
...      ...  ...
6199      NaN  ...
6200      NaN  ...
6201      NaN  ...
6202      NaN  ...
6203      NaN  ...

      2020_post_parturm_fp_4weeks_to_6weeks_re_visits  \
0      NaN
1      NaN
2      NaN
3      NaN
4      NaN
...      ...
6199      53.0

```

6200	3.0
6201	41.0
6202	NaN
6203	21.0

	2020_post_parturm_fp_within_48_hours_new_clients \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	17.0
6200	75.0
6201	191.0
6202	NaN
6203	9.0

	2020_post_parturm_fp_within_48_hours_re_visits \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	NaN
6200	54.0
6201	34.0
6202	NaN
6203	8.0

	2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	NaN
6200	NaN
6201	3.0
6202	NaN
6203	NaN

	2020_voluntary_surgical_contraception_vasectomy_re_insertion \
0	NaN
1	NaN

2	NaN
3	NaN
4	NaN
...	...
6199	NaN
6200	NaN
6201	NaN
6202	NaN
6203	NaN

	2020_voluntary_surgical_contraception_btl_ist_time_insertion \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	1.0
6200	1.0
6201	15.0
6202	NaN
6203	10.0

	2020_voluntary_surgical_contraception_btl_re_insertion \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	NaN
6200	NaN
6201	NaN
6202	NaN
6203	NaN

	population_growth_rate	total_population \
0	3.16	999367.00
1	3.02	938866.00
2	3.10	597313.00
3	1568.96	834381.70
4	4.02	3894186.00
...	...	...
6199	2.32	296179.23
6200	2.94	1153812.49
6201	2.90	2480137.33
6202	2.67	451552.75

6203 NaN 849272.42

```
women_of_childbearing_age_(15_49yrs)
0      225176.00
1      223505.00
2      144549.00
3      237820.00
4      981191.00
...
6199      67863.42
6200      277655.62
6201      651943.27
6202      113879.15
6203      213275.72
```

[6204 rows x 60 columns]

```
[10]: # Drop columns where all values are null
df_service1=df_service1.dropna(axis=1, how='all')
df_service1
```

```
[10]:   periodid  periodname  year_month  country  county \
0      201404    April 2014      201404    Kenya    Turkana County
1      201404    April 2014      201404    Kenya    Nandi County
2      201404    April 2014      201404    Kenya    West Pokot County
3      201404    April 2014      201404    Kenya    Bomet County
4      201404    April 2014      201404    Kenya    Nairobi County
...
6199    202409    September 2024      202409    Kenya    Isiolo County
6200    202409    September 2024      202409    Kenya    Trans Nzoia County
6201    202409    September 2024      202409    Kenya    Nakuru County
6202    202409    September 2024      202409    Kenya    Tharaka Nithi County
6203    202409    September 2024      202409    Kenya    Nyeri County
```

```
   uid  organisationunitname  county_code \
0  kphDeKC1Fch    Turkana County  KE_County_23
1  t0J75eHKxz5    Nandi County  KE_County_29
2  XWALbfAPa6n    West Pokot County  KE_County_24
3  HMNARUV2CW4    Bomet County  KE_County_36
4  jkG3zaihdsS    Nairobi County  KE_County_47
...
6199  bz0fj0iwdH    Isiolo County  KE_County_11
6200  mThvosEflAU    Trans Nzoia County  KE_County_26
6201  ob6SxuRcqU4    Nakuru County  KE_County_32
6202  T4urHM47nlm    Tharaka Nithi County  KE_County_13
6203  ptWVfaCIvX    Nyeri County  KE_County_19
```



	estimated_number_of_pregnant_women	fp_attendance_new_clients	...	\
0	24517.00	440.0	...	
1	43784.00	3572.0	...	
2	21198.00	745.0	...	
3	39762.00	2521.0	...	
4	158875.00	11356.0	...	
...	...	...	...	
6199	7422.28	240.0	...	
6200	35675.47	2805.0	...	
6201	78676.96	10801.0	...	
6202	13004.53	1061.0	...	
6203	19362.90	1516.0	...	

	2020_post_parturm_fp_4weeks_to_6weeks_re_visits	\
0	NaN	
1	NaN	
2	NaN	
3	NaN	
4	NaN	
...	...	
6199	53.0	
6200	3.0	
6201	41.0	
6202	NaN	
6203	21.0	

	2020_post_parturm_fp_within_48_hours_new_clients	\
0	NaN	
1	NaN	
2	NaN	
3	NaN	
4	NaN	
...	...	
6199	17.0	
6200	75.0	
6201	191.0	
6202	NaN	
6203	9.0	

	2020_post_parturm_fp_within_48_hours_re_visits	\
0	NaN	
1	NaN	
2	NaN	
3	NaN	
4	NaN	
...	...	
6199	NaN	

6200	54.0
6201	34.0
6202	NaN
6203	8.0

	2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	NaN
6200	NaN
6201	3.0
6202	NaN
6203	NaN

	2020_voluntary_surgical_contraception_vasectomy_re_insertion \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	NaN
6200	NaN
6201	NaN
6202	NaN
6203	NaN

	2020_voluntary_surgical_contraception_btl_ist_time_insertion \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
6199	1.0
6200	1.0
6201	15.0
6202	NaN
6203	10.0

	2020_voluntary_surgical_contraception_btl_re_insertion \
0	NaN
1	NaN

2	NaN
3	NaN
4	NaN
...	...
6199	NaN
6200	NaN
6201	NaN
6202	NaN
6203	NaN

	population_growth_rate	total_population \
0	3.16	999367.00
1	3.02	938866.00
2	3.10	597313.00
3	1568.96	834381.70
4	4.02	3894186.00
...	...	...
6199	2.32	296179.23
6200	2.94	1153812.49
6201	2.90	2480137.33
6202	2.67	451552.75
6203	NaN	849272.42

	women_of_childbearing_age_(15_49yrs)
0	225176.00
1	223505.00
2	144549.00
3	237820.00
4	981191.00
...	...
6199	67863.42
6200	277655.62
6201	651943.27
6202	113879.15
6203	213275.72

[6204 rows x 58 columns]

```
[11]: # Drop unwanted columns
df_service1=df_service1.drop(columns=['periodid','organisationunitname',
↳ 'periodname','population_growth_rate',
↳
↳ 'total_population','women_of_childbearing_age_(15_49yrs)']
, axis=1)
```

```
[12]: # Check for missing values
df_service1.isna().sum().sort_values(ascending=False)
```

[12]: 2020_voluntary_surgical_contraception_vasectomy_re_insertion	6199
2020_voluntary_surgical_contraception_btl_re_insertion	6172
2020_clients_given_cycle_beads_re_visits	6120
2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion	5904
2020_clients_receiving_post_abortion_fp_re_visits	5779
2020_clients_given_cycle_beads_new_clients	5016
2020_post_parturm_fp_within_48_hours_re_visits	5005
2020_post_parturm_fp_4weeks_to_6weeks_re_visits	4776
2020_iucd_insertion_hormonal_re_insertion	4643
2020_voluntary_surgical_contraception_btl_ist_time_insertion	4619
2020_clients_receiving_post_abortion_fp_new_clients	4197
2020_iucd_insertion_hormonal_ist_time_insertion	4189
2020_iucd_insertion_non_hormonal_re_insertion	4110
2020_fp_injections_dmpa_sc_re_visits	4096
2020_fp_injections_dmpa_sc_new_clients	4071
2020_post_parturm_fp_within_48_hours_new_clients	3996
2020_iucd_insertion_non_hormonal_ist_time_insertion	3872
2020_post_parturm_fp_4weeks_to_6weeks_new_clients	3854
2020_implants_insertion_1_rod_re_insertion	3815
2020_implants_insertion_2_rod_re_insertion	3802
2020_adults_25+_receiving_fp_services_re_visits	3796
2020_adults_25+_receiving_fp_services_new_clients	3789
2020_implants_insertion_2_rod_ist_time_insertion	3770
2020_implants_insertion_1_rod_ist_time_insertion	3766
2020_fp_injections_dmpa_im_new_clients	3739
2020_fp_injections_dmpa_im_re_visits	3735
clients_receiving_female_condoms_re_visits	3378
clients_counselled_natural_family_planning_re_visits	2895
adolescent_10_14_yrs_receiving_fp_services_re_visits	2877
emergency_contraceptive_pill_re_visits	2802
adolescent_10_14_yrs_receiving_fp_services_new_clients	2109
clients_receiving_female_condoms_new_clients	2063
emergency_contraceptive_pill_new_clients	1367
adolescent_15_19_yrs_receiving_fp_services_re_visits	1248
adolescent_20_24_yrs_receiving_fp_services_re_visits	1240
adolescent_20_24_yrs_receiving_fp_services_new_clients	1232
adolescent_15_19_yrs_receiving_fp_services_new_clients	1224
clients_counselled_natural_family_planning_new_clients	745
client_receiving_male_condoms_re_visits	200
pills_progestin_only_re_visits	39
estimated_number_of_pregnant_women	12
pills_progestin_only_new_clients	11
pills_combined_oral_contraceptive_re_visits	10
pills_combined_oral_contraceptive_new_clients	3
client_receiving_male_condoms_new_clients	0
fp_attendance_re_visits	0
fp_attendance_new_clients	0

```

county_code      0
uid              0
county           0
country          0
year_month       0
dtype: int64

```

Missing values were interpreted as ‘no service was provided or dataset missing for the organization unit’ and filled with 0

```

[13]: # Fill the missing values with zeros
df_service1 = df_service1.fillna(0)

```

```

[14]: # Extract year from 'year_month'
df_service1['year'] = df_service1['year_month'].astype(str).str[:4].astype(int)
df_service1

```

```

[14]:      year_month country      county      uid  county_code \
0      201404   Kenya  Turkana County  kphDeKC1Fch  KE_County_23
1      201404   Kenya    Nandi County  t0J75eHKxz5  KE_County_29
2      201404   Kenya  West Pokot County  XWALbfAPa6n  KE_County_24
3      201404   Kenya    Bomet County  HMNARUV2CW4  KE_County_36
4      201404   Kenya  Nairobi County  jkG3zaihds  KE_County_47
...      ...      ...      ...      ...      ...
6199    202409   Kenya  Isiolo County  bz0fj0iwdH  KE_County_11
6200    202409   Kenya  Trans Nzoia County  mThvosEflAU  KE_County_26
6201    202409   Kenya    Nakuru County  ob6SxuRcqU4  KE_County_32
6202    202409   Kenya  Tharaka Nithi County  T4urHM47nlm  KE_County_13
6203    202409   Kenya    Nyeri County  ptWVfaCIIdVx  KE_County_19

      estimated_number_of_pregnant_women  fp_attendance_new_clients \
0      24517.00      440.0
1      43784.00      3572.0
2      21198.00      745.0
3      39762.00      2521.0
4      158875.00     11356.0
...      ...      ...
6199      7422.28      240.0
6200     35675.47     2805.0
6201     78676.96    10801.0
6202     13004.53     1061.0
6203     19362.90     1516.0

      fp_attendance_re_visits \
0      896.0
1     7044.0
2     738.0

```

3	4411.0
4	26382.0
...	...
6199	683.0
6200	7968.0
6201	25114.0
6202	4490.0
6203	6719.0

	adolescent_10_14_yrs_receiving_fp_services_new_clients \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	1.0
6200	1.0
6201	8.0
6202	1.0
6203	5.0

	adolescent_10_14_yrs_receiving_fp_services_re_visits ... \
0	0.0 ...
1	0.0 ...
2	0.0 ...
3	0.0 ...
4	0.0 ...
...	... ...
6199	0.0 ...
6200	1.0 ...
6201	5.0 ...
6202	1.0 ...
6203	0.0 ...

	2020_implants_insertion_2_rod_re_insertion \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	71.0
6200	491.0
6201	1004.0
6202	142.0
6203	198.0

	2020_post_parturm_fp_4weeks_to_6weeks_new_clients \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	36.0
6200	424.0
6201	1214.0
6202	64.0
6203	382.0

	2020_post_parturm_fp_4weeks_to_6weeks_re_visits \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	53.0
6200	3.0
6201	41.0
6202	0.0
6203	21.0

	2020_post_parturm_fp_within_48_hours_new_clients \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	17.0
6200	75.0
6201	191.0
6202	0.0
6203	9.0

	2020_post_parturm_fp_within_48_hours_re_visits \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...

6199	0.0
6200	54.0
6201	34.0
6202	0.0
6203	8.0

	2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	0.0
6200	0.0
6201	3.0
6202	0.0
6203	0.0

	2020_voluntary_surgical_contraception_vasectomy_re_insertion \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	0.0
6200	0.0
6201	0.0
6202	0.0
6203	0.0

	2020_voluntary_surgical_contraception_btl_ist_time_insertion \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
6199	1.0
6200	1.0
6201	15.0
6202	0.0
6203	10.0

	2020_voluntary_surgical_contraception_btl_re_insertion	year
0	0.0	2014



1	0.0	2014
2	0.0	2014
3	0.0	2014
4	0.0	2014
...	...	...
6199	0.0	2024
6200	0.0	2024
6201	0.0	2024
6202	0.0	2024
6203	0.0	2024

[6204 rows x 53 columns]

```
[15]: # Create a new column (uid_code)
df_service1['uid_code'] = df_service1[
    ['year_month', 'uid' ]].astype(str).agg('_', join, axis=1)

df_service1.head()
```

```
[15]:   year_month country      county      uid  county_code \
0      201404   Kenya  Turkana County kphDeKClFch KE_County_23
1      201404   Kenya   Nandi County t0J75eHKxz5 KE_County_29
2      201404   Kenya West Pokot County XWALbfAPa6n KE_County_24
3      201404   Kenya   Bomet County HMNARUV2CW4 KE_County_36
4      201404   Kenya  Nairobi County jkG3zaihdSs KE_County_47

   estimated_number_of_pregnant_women  fp_attendance_new_clients \
0                                24517.0                        440.0
1                                43784.0                       3572.0
2                                21198.0                        745.0
3                                39762.0                       2521.0
4                                158875.0                      11356.0

   fp_attendance_re_visits \
0                        896.0
1                       7044.0
2                        738.0
3                       4411.0
4                       26382.0

   adolescent_10_14_yrs_receiving_fp_services_new_clients \
0                                0.0
1                                0.0
2                                0.0
3                                0.0
4                                0.0
```

	adolescent_10_14_yrs_receiving_fp_services_re_visits	...	\
0		0.0	...
1		0.0	...
2		0.0	...
3		0.0	...
4		0.0	...

	2020_post_parturm_fp_4weeks_to_6weeks_new_clients	\
0		0.0
1		0.0
2		0.0
3		0.0
4		0.0

	2020_post_parturm_fp_4weeks_to_6weeks_re_visits	\
0		0.0
1		0.0
2		0.0
3		0.0
4		0.0

	2020_post_parturm_fp_within_48_hours_new_clients	\
0		0.0
1		0.0
2		0.0
3		0.0
4		0.0

	2020_post_parturm_fp_within_48_hours_re_visits	\
0		0.0
1		0.0
2		0.0
3		0.0
4		0.0

	2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion	\
0		0.0
1		0.0
2		0.0
3		0.0
4		0.0

	2020_voluntary_surgical_contraception_vasectomy_re_insertion	\
0		0.0
1		0.0
2		0.0
3		0.0

```

4                                     0.0

2020_voluntary_surgical_contraception_btl_ist_time_insertion \
0                                     0.0
1                                     0.0
2                                     0.0
3                                     0.0
4                                     0.0

2020_voluntary_surgical_contraception_btl_re_insertion  year \
0                                     0.0      2014
1                                     0.0      2014
2                                     0.0      2014
3                                     0.0      2014
4                                     0.0      2014

uid_code
0  201404_kphDeKC1Fch
1  201404_t0J75eHKxz5
2  201404_XWALbfAPa6n
3  201404_HMNARUV2CW4
4  201404_jkG3zaihdsSs

```

[5 rows x 54 columns]

```

[16]: # Create a new column (uid_year)
df_service1['uid_year'] = df_service1[
    ['year', 'uid']].astype(str).agg('_', axis=1)

df_service1.head()

```

```

[16]:  year_month  country      county      uid  county_code \
0      201404   Kenya  Turkana County  kphDeKC1Fch  KE_County_23
1      201404   Kenya   Nandi County  t0J75eHKxz5  KE_County_29
2      201404   Kenya West Pokot County  XWALbfAPa6n  KE_County_24
3      201404   Kenya   Bomet County  HMNARUV2CW4  KE_County_36
4      201404   Kenya  Nairobi County  jkG3zaihdsSs  KE_County_47

estimated_number_of_pregnant_women  fp_attendance_new_clients \
0                                24517.0                    440.0
1                                43784.0                    3572.0
2                                21198.0                     745.0
3                                39762.0                    2521.0
4                                158875.0                   11356.0

fp_attendance_re_visits \
0                        896.0

```

1	7044.0
2	738.0
3	4411.0
4	26382.0

	adolescent_10_14_yrs_receiving_fp_services_new_clients	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	adolescent_10_14_yrs_receiving_fp_services_re_visits	...	\
0	0.0	...	
1	0.0	...	
2	0.0	...	
3	0.0	...	
4	0.0	...	

	2020_post_parturm_fp_4weeks_to_6weeks_re_visits	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	2020_post_parturm_fp_within_48_hours_new_clients	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	2020_post_parturm_fp_within_48_hours_re_visits	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	2020_voluntary_surgical_contraception_vasectomy_re_insertion \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

	2020_voluntary_surgical_contraception_btl_ist_time_insertion \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

	2020_voluntary_surgical_contraception_btl_re_insertion	year \
0	0.0	2014
1	0.0	2014
2	0.0	2014
3	0.0	2014
4	0.0	2014

	uid_code	uid_year
0	201404_kphDeKC1Fch	2014_kphDeKC1Fch
1	201404_t0J75eHKxz5	2014_t0J75eHKxz5
2	201404_XWALbfAPa6n	2014_XWALbfAPa6n
3	201404_HMNARUV2CW4	2014_HMNARUV2CW4
4	201404_jkG3zaihdsS	2014_jkG3zaihdsS

[5 rows x 55 columns]

```
[17]: df_service1.columns
```

```
[17]: Index(['year_month', 'country', 'county', 'uid', 'county_code',
        'estimated_number_of_pregnant_women', 'fp_attendance_new_clients',
        'fp_attendance_re_visits',
        'adolescent_10_14_yrs_receiving_fp_services_new_clients',
        'adolescent_10_14_yrs_receiving_fp_services_re_visits',
        'adolescent_15_19_yrs_receiving_fp_services_new_clients',
        'adolescent_15_19_yrs_receiving_fp_services_re_visits',
        'adolescent_20_24_yrs_receiving_fp_services_new_clients',
        'adolescent_20_24_yrs_receiving_fp_services_re_visits',
        'client_receiving_male_condoms_new_clients',
        'client_receiving_male_condoms_re_visits',
        'clients_counselled_natural_family_planning_new_clients',
        'clients_counselled_natural_family_planning_re_visits',
        'clients_receiving_female_condoms_new_clients',
        'clients_receiving_female_condoms_re_visits',
```

```

'emergency_contraceptive_pill_new_clients',
'emergency_contraceptive_pill_re_visits',
'pills_combined_oral_contraceptive_new_clients',
'pills_combined_oral_contraceptive_re_visits',
'pills_progestin_only_new_clients', 'pills_progestin_only_re_visits',
'2020_adults_25+_receiving_fp_services_new_clients',
'2020_adults_25+_receiving_fp_services_re_visits',
'2020_clients_given_cycle_beads_new_clients',
'2020_clients_given_cycle_beads_re_visits',
'2020_clients_receiving_post_abortion_fp_new_clients',
'2020_clients_receiving_post_abortion_fp_re_visits',
'2020_fp_injections_dmpa_im_new_clients',
'2020_fp_injections_dmpa_im_re_visits',
'2020_fp_injections_dmpa_sc_new_clients',
'2020_fp_injections_dmpa_sc_re_visits',
'2020_iucd_insertion_hormonal_ist_time_insertion',
'2020_iucd_insertion_hormonal_re_insertion',
'2020_iucd_insertion_non_hormonal_ist_time_insertion',
'2020_iucd_insertion_non_hormonal_re_insertion',
'2020_implants_insertion_1_rod_ist_time_insertion',
'2020_implants_insertion_1_rod_re_insertion',
'2020_implants_insertion_2_rod_ist_time_insertion',
'2020_implants_insertion_2_rod_re_insertion',
'2020_post_parturm_fp_4weeks_to_6weeks_new_clients',
'2020_post_parturm_fp_4weeks_to_6weeks_re_visits',
'2020_post_parturm_fp_within_48_hours_new_clients',
'2020_post_parturm_fp_within_48_hours_re_visits',
'2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion',
'2020_voluntary_surgical_contraception_vasectomy_re_insertion',
'2020_voluntary_surgical_contraception_btl_ist_time_insertion',
'2020_voluntary_surgical_contraception_btl_re_insertion', 'year',
'uid_code', 'uid_year'],
dtype='object')

```

```

[18]: # Check columns with float dtypes
float_cols = df_service1.select_dtypes(include=['float', 'float64']).columns
float_cols

```

```

[18]: Index(['estimated_number_of_pregnant_women', 'fp_attendance_new_clients',
'fp_attendance_re_visits',
'adolescent_10_14_yrs_receiving_fp_services_new_clients',
'adolescent_10_14_yrs_receiving_fp_services_re_visits',
'adolescent_15_19_yrs_receiving_fp_services_new_clients',
'adolescent_15_19_yrs_receiving_fp_services_re_visits',
'adolescent_20_24_yrs_receiving_fp_services_new_clients',
'adolescent_20_24_yrs_receiving_fp_services_re_visits',
'client_receiving_male_condoms_re_visits',

```

```

'clients_counselled_natural_family_planning_new_clients',
'clients_counselled_natural_family_planning_re_visits',
'clients_receiving_female_condoms_new_clients',
'clients_receiving_female_condoms_re_visits',
'emergency_contraceptive_pill_new_clients',
'emergency_contraceptive_pill_re_visits',
'pills_combined_oral_contraceptive_new_clients',
'pills_combined_oral_contraceptive_re_visits',
'pills_progestin_only_new_clients', 'pills_progestin_only_re_visits',
'2020_adults_25+_receiving_fp_services_new_clients',
'2020_adults_25+_receiving_fp_services_re_visits',
'2020_clients_given_cycle_beads_new_clients',
'2020_clients_given_cycle_beads_re_visits',
'2020_clients_receiving_post_abortion_fp_new_clients',
'2020_clients_receiving_post_abortion_fp_re_visits',
'2020_fp_injections_dmpa_im_new_clients',
'2020_fp_injections_dmpa_im_re_visits',
'2020_fp_injections_dmpa_sc_new_clients',
'2020_fp_injections_dmpa_sc_re_visits',
'2020_iucd_insertion_hormonal_ist_time_insertion',
'2020_iucd_insertion_hormonal_re_insertion',
'2020_iucd_insertion_non_hormonal_ist_time_insertion',
'2020_iucd_insertion_non_hormonal_re_insertion',
'2020_implants_insertion_1_rod_ist_time_insertion',
'2020_implants_insertion_1_rod_re_insertion',
'2020_implants_insertion_2_rod_ist_time_insertion',
'2020_implants_insertion_2_rod_re_insertion',
'2020_post_parturm_fp_4weeks_to_6weeks_new_clients',
'2020_post_parturm_fp_4weeks_to_6weeks_re_visits',
'2020_post_parturm_fp_within_48_hours_new_clients',
'2020_post_parturm_fp_within_48_hours_re_visits',
'2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion',
'2020_voluntary_surgical_contraception_vasectomy_re_insertion',
'2020_voluntary_surgical_contraception_btl_ist_time_insertion',
'2020_voluntary_surgical_contraception_btl_re_insertion'],
dtype='object')

```

```

[19]: # Convert float columns to int64
df_service1[float_cols] = df_service1[float_cols].astype('int64')

```

```

[20]: df_service1.info()

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6204 entries, 0 to 6203
Data columns (total 55 columns):
 #   Column                                     Non-
Null Count  Dtype

```

```

---  -----
-----  -----
0  year_month 6204
non-null int64
1  country 6204
non-null object
2  county 6204
non-null object
3  uid 6204
non-null object
4  county_code 6204
non-null object
5  estimated_number_of_pregnant_women 6204
non-null int64
6  fp_attendance_new_clients 6204
non-null int64
7  fp_attendance_re_visits 6204
non-null int64
8  adolescent_10_14_yrs_receiving_fp_services_new_clients 6204
non-null int64
9  adolescent_10_14_yrs_receiving_fp_services_re_visits 6204
non-null int64
10 adolescent_15_19_yrs_receiving_fp_services_new_clients 6204
non-null int64
11 adolescent_15_19_yrs_receiving_fp_services_re_visits 6204
non-null int64
12 adolescent_20_24_yrs_receiving_fp_services_new_clients 6204
non-null int64
13 adolescent_20_24_yrs_receiving_fp_services_re_visits 6204
non-null int64
14 client_receiving_male_condoms_new_clients 6204
non-null int64
15 client_receiving_male_condoms_re_visits 6204
non-null int64
16 clients_counselled_natural_family_planning_new_clients 6204
non-null int64
17 clients_counselled_natural_family_planning_re_visits 6204
non-null int64
18 clients_receiving_female_condoms_new_clients 6204
non-null int64
19 clients_receiving_female_condoms_re_visits 6204
non-null int64
20 emergency_contraceptive_pill_new_clients 6204
non-null int64
21 emergency_contraceptive_pill_re_visits 6204
non-null int64
22 pills_combined_oral_contraceptive_new_clients 6204
non-null int64

```



23	pills_combined_oral_contraceptive_re_visits	6204
non-null	int64	
24	pills_progestin_only_new_clients	6204
non-null	int64	
25	pills_progestin_only_re_visits	6204
non-null	int64	
26	2020_adults_25+_receiving_fp_services_new_clients	6204
non-null	int64	
27	2020_adults_25+_receiving_fp_services_re_visits	6204
non-null	int64	
28	2020_clients_given_cycle_beads_new_clients	6204
non-null	int64	
29	2020_clients_given_cycle_beads_re_visits	6204
non-null	int64	
30	2020_clients_receiving_post_abortion_fp_new_clients	6204
non-null	int64	
31	2020_clients_receiving_post_abortion_fp_re_visits	6204
non-null	int64	
32	2020_fp_injections_dmpa__im_new_clients	6204
non-null	int64	
33	2020_fp_injections_dmpa__im_re_visits	6204
non-null	int64	
34	2020_fp_injections_dmpa__sc_new_clients	6204
non-null	int64	
35	2020_fp_injections_dmpa__sc_re_visits	6204
non-null	int64	
36	2020_iucd_insertion_hormonal_ist_time_insertion	6204
non-null	int64	
37	2020_iucd_insertion_hormonal_re_insertion	6204
non-null	int64	
38	2020_iucd_insertion_non_hormonal_ist_time_insertion	6204
non-null	int64	
39	2020_iucd_insertion_non_hormonal_re_insertion	6204
non-null	int64	
40	2020_implants_insertion_1_rod_ist_time_insertion	6204
non-null	int64	
41	2020_implants_insertion_1_rod_re_insertion	6204
non-null	int64	
42	2020_implants_insertion_2_rod_ist_time_insertion	6204
non-null	int64	
43	2020_implants_insertion_2_rod_re_insertion	6204
non-null	int64	
44	2020_post_parturm_fp_4weeks_to_6weeks_new_clients	6204
non-null	int64	
45	2020_post_parturm_fp_4weeks_to_6weeks_re_visits	6204
non-null	int64	
46	2020_post_parturm_fp_within_48_hours_new_clients	6204
non-null	int64	

```

47 2020_post_parturm_fp_within_48_hours_re_visits 6204
non-null int64
48 2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion 6204
non-null int64
49 2020_voluntary_surgical_contraception_vasectomy_re_insertion 6204
non-null int64
50 2020_voluntary_surgical_contraception_btl_ist_time_insertion 6204
non-null int64
51 2020_voluntary_surgical_contraception_btl_re_insertion 6204
non-null int64
52 year 6204
non-null int32
53 uid_code 6204
non-null object
54 uid_year 6204
non-null object
dtypes: int32(1), int64(48), object(6)
memory usage: 2.6+ MB

```

### 3.1.2 2. ke\_fp\_commodity\_data.csv

```
[21]: # Make a copy of the data
df_commodity1 = df_commodity.copy()
```

```
[22]: # Preview the data
df_commodity1.head()
```

```
[22]:
```

	periodid	periodname	periodcode	perioddescription	orgunitlevel1	\
0	201404	14-Apr	201404	NaN	Kenya	
1	201404	14-Apr	201404	NaN	Kenya	
2	201404	14-Apr	201404	NaN	Kenya	
3	201404	14-Apr	201404	NaN	Kenya	
4	201404	14-Apr	201404	NaN	Kenya	

	orgunitlevel2	organisationunitid	organisationunitname	\
0	Kirinyaga County	Ulj33KBau7V	Kirinyaga County	
1	Kisii County	sPkRcDvhGWA	Kisii County	
2	Kisumu County	tAbBVBbueqD	Kisumu County	
3	Makueni County	BoDytkJQ4Qi	Makueni County	
4	Kwale County	N7YETT3A9r1	Kwale County	

	organisationunitcode	organisationunitdescription	...	\
0	KE_County_20	NaN	...	
1	KE_County_45	NaN	...	
2	KE_County_42	NaN	...	
3	KE_County_17	NaN	...	
4	KE_County_2	NaN	...	

	implants_stock_losses	implants_stock_dispensed	implants_stock_at_hand	\
0	0	223	1670	
1	0	6	14	
2	1	151	1719	
3	0	31	89	
4	1	94	1224	

	implants_stock_requested	implants_stock_received	iud_stock_losses	\
0	245	30	1	
1	70	20	0	
2	100	0	0	
3	50	40	0	
4	250	53	1	

	iud_stock_dispensed	iud_stock_at_hand	iud_stock_requested	\
0	253	1445	368	
1	0	0	20	
2	20	78	220	
3	2	289	20	
4	7	444	25	

	iud_stock_received
0	30
1	0
2	0
3	0
4	0

[5 rows x 50 columns]

```
[23]: # Explore the data
df_commodity1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2480 entries, 0 to 2479
```

```
Data columns (total 50 columns):
```

#	Column	Non-Null Count	Dtype
0	periodid	2480 non-null	int64
1	periodname	2480 non-null	object
2	periodcode	2480 non-null	int64
3	perioddescription	0 non-null	float64
4	orgunitlevel1	2480 non-null	object
5	orgunitlevel2	2480 non-null	object
6	organisationunitid	2480 non-null	object
7	organisationunitname	2480 non-null	object

8	organisationunitcode	2480 non-null	object
9	organisationunitdescription	0 non-null	float64
10	pills_combined_oral_contraceptive_stock_losses	2480 non-null	int64
11	pills_combined_oral_contraceptive_stock_dispensed	2480 non-null	int64
12	pills_combined_oral_contraceptive_stock_at_hand	2480 non-null	int64
13	pills_combined_oral_contraceptive_stock_requested	2480 non-null	int64
14	pills_combined_oral_contraceptive_stock_received	2480 non-null	int64
15	pills_emergency_pill_stock_losses	2480 non-null	int64
16	pills_emergency_pill_stock_dispensed	2480 non-null	int64
17	pills_emergency_pill_stock_at_hand	2480 non-null	int64
18	pills_emergency_pill_stock_requested	2480 non-null	int64
19	pills_emergency_pill_stock_received	2480 non-null	int64
20	pills_progestin_only_pills_stock_losses	2480 non-null	int64
21	pills_progestin_only_pills_stock_dispensed	2480 non-null	int64
22	pills_progestin_only_pills_stock_at_hand	2480 non-null	int64
23	pills_progestin_only_pills_stock_requested	2480 non-null	int64
24	pills_progestin_only_pills_stock_received	2480 non-null	int64
25	condoms_female_condom_stock_losses	2480 non-null	int64
26	condoms_female_condom_stock_dispensed	2480 non-null	int64
27	condoms_female_condom_stock_at_hand	2480 non-null	int64
28	condoms_female_condom_stock_requested	2480 non-null	int64
29	condoms_female_condom_stock_received	2480 non-null	int64
30	condoms_male_condom_stock_losses	2480 non-null	int64
31	condoms_male_condom_stock_dispensed	2480 non-null	int64
32	condoms_male_condom_stock_at_hand	2480 non-null	int64
33	condoms_male_condom_stock_requested	2480 non-null	int64
34	condoms_male_condom_stock_received	2480 non-null	int64
35	injectables_stock_losses	2480 non-null	int64
36	injectables_stock_dispensed	2480 non-null	int64
37	injectables_stock_at_hand	2480 non-null	int64
38	injectables_stock_requested	2480 non-null	int64
39	injectables_stock_received	2480 non-null	int64
40	implants_stock_losses	2480 non-null	int64
41	implants_stock_dispensed	2480 non-null	int64
42	implants_stock_at_hand	2480 non-null	int64
43	implants_stock_requested	2480 non-null	int64
44	implants_stock_received	2480 non-null	int64
45	iud_stock_losses	2480 non-null	int64
46	iud_stock_dispensed	2480 non-null	int64
47	iud_stock_at_hand	2480 non-null	int64
48	iud_stock_requested	2480 non-null	int64
49	iud_stock_received	2480 non-null	int64

dtypes: float64(2), int64(42), object(6)

memory usage: 968.9+ KB

```
[24]: # Standardize the column names
df_commodity1 = standardize_col_labels(df_commodity1)
```

```
df_commodity1.head()
```

```
[24]:
```

	periodid	periodname	periodcode	perioddescription	orgunitlevel1	\
0	201404	14-Apr	201404	NaN	Kenya	
1	201404	14-Apr	201404	NaN	Kenya	
2	201404	14-Apr	201404	NaN	Kenya	
3	201404	14-Apr	201404	NaN	Kenya	
4	201404	14-Apr	201404	NaN	Kenya	

	orgunitlevel2	organisationunitid	organisationunitname	\
0	Kirinyaga County	Ulj33KBau7V	Kirinyaga County	
1	Kisii County	sPkRcDvhGWA	Kisii County	
2	Kisumu County	tAbBVBbueqD	Kisumu County	
3	Makueni County	BoDytkJQ4Qi	Makueni County	
4	Kwale County	N7YETT3A9r1	Kwale County	

	organisationunitcode	organisationunitdescription	...	\
0	KE_County_20	NaN	...	
1	KE_County_45	NaN	...	
2	KE_County_42	NaN	...	
3	KE_County_17	NaN	...	
4	KE_County_2	NaN	...	

	implants_stock_losses	implants_stock_dispensed	implants_stock_at_hand	\
0	0	223	1670	
1	0	6	14	
2	1	151	1719	
3	0	31	89	
4	1	94	1224	

	implants_stock_requested	implants_stock_received	iud_stock_losses	\
0	245	30	1	
1	70	20	0	
2	100	0	0	
3	50	40	0	
4	250	53	1	

	iud_stock_dispensed	iud_stock_at_hand	iud_stock_requested	\
0	253	1445	368	
1	0	0	20	
2	20	78	220	
3	2	289	20	
4	7	444	25	

	iud_stock_received
0	30

```

1          0
2          0
3          0
4          0

```

[5 rows x 50 columns]

```

[25]: # Rename column names
df_commodity1 = df_commodity1.rename(columns=name_map)
df_commodity1

```

```

[25]:      periodid periodname  year_month  perioddescription  country  \
0      201404      14-Apr      201404                NaN  Kenya
1      201404      14-Apr      201404                NaN  Kenya
2      201404      14-Apr      201404                NaN  Kenya
3      201404      14-Apr      201404                NaN  Kenya
4      201404      14-Apr      201404                NaN  Kenya
...      ...      ...      ...      ...      ...
2475    202209      22-Sep      202209                NaN  Kenya
2476    202209      22-Sep      202209                NaN  Kenya
2477    202209      22-Sep      202209                NaN  Kenya
2478    202309      23-Sep      202309                NaN  Kenya
2479    202409      24-Sep      202409                NaN  Kenya

      county      uid organisationunitname  county_code  \
0  Kirinyaga County  Ulj33KBau7V  Kirinyaga County  KE_County_20
1    Kisii County  sPkRcDvhGWA    Kisii County  KE_County_45
2    Kisumu County  tAbBVBbueqD    Kisumu County  KE_County_42
3  Makueni County  BoDytkJQ4Qi  Makueni County  KE_County_17
4    Kwale County  N7YETT3A9r1    Kwale County  KE_County_2
...      ...      ...      ...      ...
2475  Kericho County  ihZsJ8alvtb  Kericho County  KE_County_35
2476    Nandi County  t0J75eHKxz5    Nandi County  KE_County_29
2477  Machakos County  yhCUgGcCcOo  Machakos County  KE_County_16
2478  Nairobi County  jkG3zaihds  Nairobi County  KE_County_47
2479  Nairobi County  jkG3zaihds  Nairobi County  KE_County_47

      organisationunitdescription  ...  implants_stock_losses  \
0                NaN  ...                0
1                NaN  ...                0
2                NaN  ...                1
3                NaN  ...                0
4                NaN  ...                1
...      ...      ...      ...
2475                NaN  ...                0
2476                NaN  ...                0
2477                NaN  ...                0

```

2478	NaN	...	0
2479	NaN	...	0

	implants_stock_dispensed	implants_stock_at_hand \
0	223	1670
1	6	14
2	151	1719
3	31	89
4	94	1224
...	...	...
2475	0	0
2476	0	0
2477	0	0
2478	0	0
2479	0	6

	implants_stock_requested	implants_stock_received	iud_stock_losses \
0	245	30	1
1	70	20	0
2	100	0	0
3	50	40	0
4	250	53	1
...	...	...	...
2475	300	0	0
2476	500	0	0
2477	0	0	0
2478	0	0	0
2479	0	6	0

	iud_stock_dispensed	iud_stock_at_hand	iud_stock_requested \
0	253	1445	368
1	0	0	20
2	20	78	220
3	2	289	20
4	7	444	25
...	...	...	...
2475	0	0	0
2476	0	0	0
2477	0	0	0
2478	2	21	0
2479	3	7	0

	iud_stock_received
0	30
1	0
2	0
3	0

```

4          0
...
2475      0
2476      0
2477      0
2478      0
2479      0

```

[2480 rows x 50 columns]

```

[26]: # Drop columns where all values are null
df_commodity1=df_commodity1.dropna(axis=1, how='all')
df_commodity1

```

```

[26]:      periodid periodname  year_month country      county      uid \
0      201404      14-Apr      201404  Kenya  Kirinyaga County  Ulj33KBau7V
1      201404      14-Apr      201404  Kenya    Kisii County  sPkRcDvhGWA
2      201404      14-Apr      201404  Kenya    Kisumu County  tAbBVBbueqD
3      201404      14-Apr      201404  Kenya  Makueni County  BoDytkJQ4Qi
4      201404      14-Apr      201404  Kenya    Kwale County  N7YETT3A9r1
...      ...      ...      ...      ...      ...      ...
2475    202209      22-Sep      202209  Kenya  Kericho County  ihZsJ8alvtb
2476    202209      22-Sep      202209  Kenya    Nandi County  t0J75eHKxz5
2477    202209      22-Sep      202209  Kenya  Machakos County  yhCUgGcCcOo
2478    202309      23-Sep      202309  Kenya  Nairobi County  jkG3zaihds
2479    202409      24-Sep      202409  Kenya  Nairobi County  jkG3zaihds

```

```

      organisationunitname  county_code \
0      Kirinyaga County  KE_County_20
1      Kisii County  KE_County_45
2      Kisumu County  KE_County_42
3      Makueni County  KE_County_17
4      Kwale County  KE_County_2
...      ...      ...
2475    Kericho County  KE_County_35
2476    Nandi County  KE_County_29
2477    Machakos County  KE_County_16
2478    Nairobi County  KE_County_47
2479    Nairobi County  KE_County_47

```

```

      pills_combined_oral_contraceptive_stock_losses \
0          0
1          0
2         17
3        135
4         13
...      ...

```



2475	0
2476	0
2477	0
2478	0
2479	0

	pills_combined_oral_contraceptive_stock_dispensed	...	\
0	5728	...	
1	8	...	
2	241	...	
3	149	...	
4	693	...	
...	...	...	
2475	0	...	
2476	420	...	
2477	3653	...	
2478	0	...	
2479	22	...	

	implants_stock_losses	implants_stock_dispensed	implants_stock_at_hand	\
0	0	223	1670	
1	0	6	14	
2	1	151	1719	
3	0	31	89	
4	1	94	1224	
...	...	...	...	
2475	0	0	0	
2476	0	0	0	
2477	0	0	0	
2478	0	0	0	
2479	0	0	6	

	implants_stock_requested	implants_stock_received	iud_stock_losses	\
0	245	30	1	
1	70	20	0	
2	100	0	0	
3	50	40	0	
4	250	53	1	
...	...	...	...	
2475	300	0	0	
2476	500	0	0	
2477	0	0	0	
2478	0	0	0	
2479	0	6	0	

	iud_stock_dispensed	iud_stock_at_hand	iud_stock_requested	\
0	253	1445	368	

1	0	0	20
2	20	78	220
3	2	289	20
4	7	444	25
...	...	...	...
2475	0	0	0
2476	0	0	0
2477	0	0	0
2478	2	21	0
2479	3	7	0

iud_stock_received	
0	30
1	0
2	0
3	0
4	0
...	...
2475	0
2476	0
2477	0
2478	0
2479	0

[2480 rows x 48 columns]

```
[27]: # Drop unwanted columns
df_commodity1.drop(columns='organisationunitname', inplace=True)
df_commodity1
```

c:\Users\User\anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:4163: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
return super().drop(

```
[27]:
```

	periodid	periodname	year_month	country	county	uid \
0	201404	14-Apr	201404	Kenya	Kirinyaga County	UlJ33KBau7V
1	201404	14-Apr	201404	Kenya	Kisii County	sPkRcDvhGWA
2	201404	14-Apr	201404	Kenya	Kisumu County	tAbBVBbueqD
3	201404	14-Apr	201404	Kenya	Makueni County	BoDytkJQ4Qi
4	201404	14-Apr	201404	Kenya	Kwale County	N7YETT3A9r1
...	...	...	...	...	...	...
2475	202209	22-Sep	202209	Kenya	Kericho County	ihZsJ8alvtb
2476	202209	22-Sep	202209	Kenya	Nandi County	t0J75eHKxz5

2477	202209	22-Sep	202209	Kenya	Machakos County	yhCUgGcCc0o
2478	202309	23-Sep	202309	Kenya	Nairobi County	jkG3zaihds
2479	202409	24-Sep	202409	Kenya	Nairobi County	jkG3zaihds

	county_code	pills_combined_oral_contraceptive_stock_losses	\
0	KE_County_20	0	
1	KE_County_45	0	
2	KE_County_42	17	
3	KE_County_17	135	
4	KE_County_2	13	
...	...	...	
2475	KE_County_35	0	
2476	KE_County_29	0	
2477	KE_County_16	0	
2478	KE_County_47	0	
2479	KE_County_47	0	

	pills_combined_oral_contraceptive_stock_dispensed	\
0	5728	
1	8	
2	241	
3	149	
4	693	
...	...	
2475	0	
2476	420	
2477	3653	
2478	0	
2479	22	

	pills_combined_oral_contraceptive_stock_at_hand	...	\
0	46036	...	
1	58	...	
2	3542	...	
3	2588	...	
4	9289	...	
...	...	...	
2475	0	...	
2476	43	...	
2477	46174	...	
2478	60	...	
2479	208	...	

	implants_stock_losses	implants_stock_dispensed	implants_stock_at_hand	\
0	0	223	1670	
1	0	6	14	
2	1	151	1719	

3	0	31	89
4	1	94	1224
...	...	...	...
2475	0	0	0
2476	0	0	0
2477	0	0	0
2478	0	0	0
2479	0	0	6

	implants_stock_requested	implants_stock_received	iud_stock_losses	\
0	245	30	1	
1	70	20	0	
2	100	0	0	
3	50	40	0	
4	250	53	1	
...	...	...	...	
2475	300	0	0	
2476	500	0	0	
2477	0	0	0	
2478	0	0	0	
2479	0	6	0	

	iud_stock_dispensed	iud_stock_at_hand	iud_stock_requested	\
0	253	1445	368	
1	0	0	20	
2	20	78	220	
3	2	289	20	
4	7	444	25	
...	...	...	...	
2475	0	0	0	
2476	0	0	0	
2477	0	0	0	
2478	2	21	0	
2479	3	7	0	

	iud_stock_received
0	30
1	0
2	0
3	0
4	0
...	...
2475	0
2476	0
2477	0
2478	0
2479	0

[2480 rows x 47 columns]

```
[28]: # Check for missing values
df_commodity1.isna().sum().sort_values(ascending=False)
```

```
[28]: iud_stock_received                                0
pills_combined_oral_contraceptive_stock_received    0
pills_progestin_only_pills_stock_requested           0
pills_progestin_only_pills_stock_at_hand            0
pills_progestin_only_pills_stock_dispensed          0
pills_progestin_only_pills_stock_losses             0
pills_emergency_pill_stock_received                 0
pills_emergency_pill_stock_requested                0
pills_emergency_pill_stock_at_hand                  0
pills_emergency_pill_stock_dispensed                0
pills_emergency_pill_stock_losses                   0
pills_combined_oral_contraceptive_stock_requested    0
condoms_female_condom_stock_losses                  0
pills_combined_oral_contraceptive_stock_at_hand     0
pills_combined_oral_contraceptive_stock_dispensed   0
pills_combined_oral_contraceptive_stock_losses      0
county_code                                          0
uid                                                  0
county                                               0
country                                              0
year_month                                           0
periodname                                           0
pills_progestin_only_pills_stock_received           0
condoms_female_condom_stock_dispensed               0
iud_stock_requested                                 0
injectables_stock_requested                         0
iud_stock_at_hand                                   0
iud_stock_dispensed                                 0
iud_stock_losses                                    0
implants_stock_received                             0
implants_stock_requested                           0
implants_stock_at_hand                             0
implants_stock_dispensed                           0
implants_stock_losses                              0
injectables_stock_received                          0
injectables_stock_at_hand                           0
condoms_female_condom_stock_at_hand                 0
injectables_stock_dispensed                         0
injectables_stock_losses                           0
condoms_male_condom_stock_received                  0
condoms_male_condom_stock_requested                 0
```

```

condoms_male_condom_stock_at_hand          0
condoms_male_condom_stock_dispensed         0
condoms_male_condom_stock_losses            0
condoms_female_condom_stock_received        0
condoms_female_condom_stock_requested       0
periodid                                    0
dtype: int64

```

The missing values were interpreted as ‘no event reported’

```

[29]: # Dealing with the missing values

df_commodity1 = df_commodity1.fillna(0)

```

```

[30]: # Check for duplicates
df_commodity1.duplicated().sum()

```

```

[30]: 0

```

A new column(uid\_code) was created by concatenating the year\_month column and organisation unit id

```

[31]: # Create a new column (uid_code)
df_commodity1['uid_code'] = df_commodity1[['year_month', 'uid' ]].astype(str).
    ↪agg('_', join, axis=1)

df_commodity1.head()

```

```

[31]:
periodid  periodname  year_month  country  county  uid \
0    201404    14-Apr    201404    Kenya  Kirinyaga County  U1j33KBau7V
1    201404    14-Apr    201404    Kenya  Kisii County    sPkRcDvhGWA
2    201404    14-Apr    201404    Kenya  Kisumu County    tAbBVBbueqD
3    201404    14-Apr    201404    Kenya  Makueni County   BoDytkJQ4Qi
4    201404    14-Apr    201404    Kenya  Kwale County     N7YETT3A9r1

```

```

county_code  pills_combined_oral_contraceptive_stock_losses \
0  KE_County_20                                           0
1  KE_County_45                                           0
2  KE_County_42                                           17
3  KE_County_17                                          135
4  KE_County_2                                           13

```

```

pills_combined_oral_contraceptive_stock_dispensed \
0                                           5728
1                                           8
2                                           241
3                                           149
4                                           693

```

	pills_combined_oral_contraceptive_stock_at_hand	...	\
0	46036	...	
1	58	...	
2	3542	...	
3	2588	...	
4	9289	...	

	implants_stock_dispensed	implants_stock_at_hand	implants_stock_requested	\
0	223	1670	245	
1	6	14	70	
2	151	1719	100	
3	31	89	50	
4	94	1224	250	

	implants_stock_received	iud_stock_losses	iud_stock_dispensed	\
0	30	1	253	
1	20	0	0	
2	0	0	20	
3	40	0	2	
4	53	1	7	

	iud_stock_at_hand	iud_stock_requested	iud_stock_received	\
0	1445	368	30	
1	0	20	0	
2	78	220	0	
3	289	20	0	
4	444	25	0	

	uid_code
0	201404_Ulj33KBau7V
1	201404_sPkrCdvhGWA
2	201404_tAbBVBbueqD
3	201404_BoDytkJQ4Qi
4	201404_N7YETT3A9r1

[5 rows x 48 columns]

```
[32]: # Convert float columns to int64
float_cols_com = df_commodity1.select_dtypes(include=['float', 'float64']).
    ↪columns
df_commodity1[float_cols_com] = df_commodity1[float_cols_com].astype('int64')
df_commodity1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2480 entries, 0 to 2479
Data columns (total 48 columns):
```

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	periodid	2480 non-null	int64
1	periodname	2480 non-null	object
2	year_month	2480 non-null	int64
3	country	2480 non-null	object
4	county	2480 non-null	object
5	uid	2480 non-null	object
6	county_code	2480 non-null	object
7	pills_combined_oral_contraceptive_stock_losses	2480 non-null	int64
8	pills_combined_oral_contraceptive_stock_dispensed	2480 non-null	int64
9	pills_combined_oral_contraceptive_stock_at_hand	2480 non-null	int64
10	pills_combined_oral_contraceptive_stock_requested	2480 non-null	int64
11	pills_combined_oral_contraceptive_stock_received	2480 non-null	int64
12	pills_emergency_pill_stock_losses	2480 non-null	int64
13	pills_emergency_pill_stock_dispensed	2480 non-null	int64
14	pills_emergency_pill_stock_at_hand	2480 non-null	int64
15	pills_emergency_pill_stock_requested	2480 non-null	int64
16	pills_emergency_pill_stock_received	2480 non-null	int64
17	pills_progestin_only_pills_stock_losses	2480 non-null	int64
18	pills_progestin_only_pills_stock_dispensed	2480 non-null	int64
19	pills_progestin_only_pills_stock_at_hand	2480 non-null	int64
20	pills_progestin_only_pills_stock_requested	2480 non-null	int64
21	pills_progestin_only_pills_stock_received	2480 non-null	int64
22	condoms_female_condom_stock_losses	2480 non-null	int64
23	condoms_female_condom_stock_dispensed	2480 non-null	int64
24	condoms_female_condom_stock_at_hand	2480 non-null	int64
25	condoms_female_condom_stock_requested	2480 non-null	int64
26	condoms_female_condom_stock_received	2480 non-null	int64
27	condoms_male_condom_stock_losses	2480 non-null	int64
28	condoms_male_condom_stock_dispensed	2480 non-null	int64
29	condoms_male_condom_stock_at_hand	2480 non-null	int64
30	condoms_male_condom_stock_requested	2480 non-null	int64
31	condoms_male_condom_stock_received	2480 non-null	int64
32	injectables_stock_losses	2480 non-null	int64
33	injectables_stock_dispensed	2480 non-null	int64
34	injectables_stock_at_hand	2480 non-null	int64
35	injectables_stock_requested	2480 non-null	int64
36	injectables_stock_received	2480 non-null	int64
37	implants_stock_losses	2480 non-null	int64
38	implants_stock_dispensed	2480 non-null	int64
39	implants_stock_at_hand	2480 non-null	int64
40	implants_stock_requested	2480 non-null	int64
41	implants_stock_received	2480 non-null	int64
42	iud_stock_losses	2480 non-null	int64
43	iud_stock_dispensed	2480 non-null	int64
44	iud_stock_at_hand	2480 non-null	int64
45	iud_stock_requested	2480 non-null	int64



```

46 iud_stock_received          2480 non-null    int64
47 uid_code                    2480 non-null    object
dtypes: int64(42), object(6)
memory usage: 930.1+ KB

```

### 3.1.3 3. ke\_fp\_population\_data

```
[33]: # Make a copy of the data
df_population1 = df_population.copy()
```

```
[34]: # Standardize column names
df_population1 = standardize_col_labels(df_population1)

# Preview the data
df_population1.head()
```

```
[34]:
```

	periodid	periodname	periodcode	perioddescription	orgunitlevel1	\
0	2014	2014	2014		NaN	Kenya
1	2014	2014	2014		NaN	Kenya
2	2014	2014	2014		NaN	Kenya
3	2014	2014	2014		NaN	Kenya
4	2014	2014	2014		NaN	Kenya

	orgunitlevel2	organisationunitid	organisationunitname	\
0	Kajiado County	Hsk1YV8kHkT	Kajiado County	
1	Laikipia County	xuFdFy6t9AH	Laikipia County	
2	Turkana County	kphDeKC1Fch	Turkana County	
3	Nandi County	t0J75eHKxz5	Nandi County	
4	Elgeyo Marakwet County	MqnLxQBigG0	Elgeyo Marakwet County	

	organisationunitcode	organisationunitdescription	\
0	KE_County_34		NaN
1	KE_County_31		NaN
2	KE_County_23		NaN
3	KE_County_29		NaN
4	KE_County_28		NaN

	estimated_number_of_pregnant_women	population_10_14_year_old_girls	\
0	30521.0		NaN
1	12362.0		NaN
2	24517.0		NaN
3	43784.0		NaN
4	18424.0		NaN

	women_of_childbearing_age_(15_49yrs)	uid_code	uid_year	\
0	174354.0	201401_Hsk1YV8kHkT	2014_Hsk1YV8kHkT	
1	68426.0	201401_xuFdFy6t9AH	2014_xuFdFy6t9AH	

2		225176.0	201401_kphDeKC1Fch	2014_kphDeKC1Fch
3		223505.0	201401_t0J75eHKxz5	2014_t0J75eHKxz5
4		103238.0	201401_MqnLxQBigG0	2014_MqnLxQBigG0

	unnamed:_15	unnamed:_16	unnamed:_17	unnamed:_18
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

```
[35]: # Rename column names
df_population1 = df_population1.rename(columns=name_map)

df_population1.head()
```

```
[35]:
```

	periodid	periodname	year_month	perioddescription	country	\
0	2014	2014	2014	NaN	Kenya	
1	2014	2014	2014	NaN	Kenya	
2	2014	2014	2014	NaN	Kenya	
3	2014	2014	2014	NaN	Kenya	
4	2014	2014	2014	NaN	Kenya	

	county	uid	organisationunitname	county_code	\
0	Kajiado County	Hsk1YV8kHkT	Kajiado County	KE_County_34	
1	Laikipia County	xuFdFy6t9AH	Laikipia County	KE_County_31	
2	Turkana County	kphDeKC1Fch	Turkana County	KE_County_23	
3	Nandi County	t0J75eHKxz5	Nandi County	KE_County_29	
4	Elgeyo Marakwet County	MqnLxQBigG0	Elgeyo Marakwet County	KE_County_28	

	organisationunitdescription	estimated_number_of_pregnant_women	\
0	NaN	30521.0	
1	NaN	12362.0	
2	NaN	24517.0	
3	NaN	43784.0	
4	NaN	18424.0	

	population_10_14_year_old_girls	women_of_childbearing_age_(15_49yrs)	\
0	NaN	174354.0	
1	NaN	68426.0	
2	NaN	225176.0	
3	NaN	223505.0	
4	NaN	103238.0	

	uid_code	uid_year	unnamed:_15	unnamed:_16	\
0	201401_Hsk1YV8kHkT	2014_Hsk1YV8kHkT	NaN	NaN	
1	201401_xuFdFy6t9AH	2014_xuFdFy6t9AH	NaN	NaN	

2	201401_kphDeKC1Fch	2014_kphDeKC1Fch	NaN	NaN
3	201401_t0J75eHKxz5	2014_t0J75eHKxz5	NaN	NaN
4	201401_MqnLxQBigG0	2014_MqnLxQBigG0	NaN	NaN

	unnamed:_17	unnamed:_18
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

```
[36]: # Drop unwanted columns
df_population1.drop(columns=['organisationunitname'], axis=1) # This was
↳dropped because it is the same as county
```

```
[36]:      periodid  periodname  year_month  perioddescription  country \
0         2014         2014         2014                NaN  Kenya
1         2014         2014         2014                NaN  Kenya
2         2014         2014         2014                NaN  Kenya
3         2014         2014         2014                NaN  Kenya
4         2014         2014         2014                NaN  Kenya
..         ...         ...         ...                ...  ...
512        2024         2024         2024                NaN  Kenya
513        2024         2024         2024                NaN  Kenya
514        2024         2024         2024                NaN  Kenya
515        2024         2024         2024                NaN  Kenya
516        2024         2024         2024                NaN  Kenya
```

		county	uid	county_code	\
0		Kajiado County	Hsk1YV8kHkT	KE_County_34	
1		Laikipia County	xuFdFy6t9AH	KE_County_31	
2		Turkana County	kphDeKC1Fch	KE_County_23	
3		Nandi County	t0J75eHKxz5	KE_County_29	
4	Elgeyo	Marakwet County	MqnLxQBigG0	KE_County_28	
..		...	...	...	
512		Makueni County	BoDytkJQ4Qi	KE_County_17	
513		Kajiado County	Hsk1YV8kHkT	KE_County_34	
514		Kakamega County	BjC1xL40gHo	KE_County_37	
515		Muranga County	ahwTMNAJvrL	KE_County_21	
516		Nairobi County	jkG3zaihds	KE_County_47	

	organisationunitdescription	estimated_number_of_pregnant_women	\
0	NaN	30521.0	
1	NaN	12362.0	
2	NaN	24517.0	
3	NaN	43784.0	
4	NaN	18424.0	

..	...	...
512	NaN	26248.0
513	NaN	43539.0
514	NaN	71817.0
515	NaN	25812.0
516	NaN	175438.0

	population_10_14_year_old_girls	women_of_childbearing_age_(15_49yrs)	\
0	NaN	174354.0	
1	NaN	68426.0	
2	NaN	225176.0	
3	NaN	223505.0	
4	NaN	103238.0	
..	...	...	
512	59388.0	253333.0	
513	77142.0	354857.0	
514	172301.0	523862.0	
515	53629.0	280830.0	
516	227708.0	1664602.0	

	uid_code	uid_year	unnamed:_15	unnamed:_16	\
0	201401_Hsk1YV8kHkT	2014_Hsk1YV8kHkT	NaN	NaN	
1	201401_xuFdFy6t9AH	2014_xuFdFy6t9AH	NaN	NaN	
2	201401_kphDeKC1Fch	2014_kphDeKC1Fch	NaN	NaN	
3	201401_t0J75eHKxz5	2014_t0J75eHKxz5	NaN	NaN	
4	201401_MqnLxQBigG0	2014_MqnLxQBigG0	NaN	NaN	
..	...	...	...	...	
512	202401_BoDytkJQ4Qi	2024_BoDytkJQ4Qi	NaN	NaN	
513	202401_Hsk1YV8kHkT	2024_Hsk1YV8kHkT	NaN	NaN	
514	202401_BjC1xL40gHo	2024_BjC1xL40gHo	NaN	NaN	
515	202401_ahwTMNAJvrL	2024_ahwTMNAJvrL	NaN	NaN	
516	202401_jkG3zaihdsS	2024_jkG3zaihdsS	NaN	NaN	

	unnamed:_17	unnamed:_18
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN
..	...	...
512	NaN	NaN
513	NaN	NaN
514	NaN	NaN
515	NaN	NaN
516	NaN	NaN

[517 rows x 18 columns]

## Calculate Women eligible for FP

```
[37]: # Insert the new column, treating NaN values as 0 during the calculation
df_population1['eligible_fp'] = (
    df_population1['women_of_childbearing_age_(15_49yrs)']
    .add(df_population1['population_10_14_year_old_girls'], fill_value=0)
    .sub(df_population1['estimated_number_of_pregnant_women'], fill_value=0)
)

# Display the updated DataFrame
df_population1.head()
```

```
[37]:
```

	periodid	periodname	year_month	perioddescription	country	\
0	2014	2014	2014		NaN	Kenya
1	2014	2014	2014		NaN	Kenya
2	2014	2014	2014		NaN	Kenya
3	2014	2014	2014		NaN	Kenya
4	2014	2014	2014		NaN	Kenya

	county	uid	organisationunitname	county_code	\
0	Kajiado County	Hsk1YV8kHkT	Kajiado County	KE_County_34	
1	Laikipia County	xuFdFy6t9AH	Laikipia County	KE_County_31	
2	Turkana County	kphDeKC1Fch	Turkana County	KE_County_23	
3	Nandi County	t0J75eHKxz5	Nandi County	KE_County_29	
4	Elgeyo Marakwet County	MqnLxQBigG0	Elgeyo Marakwet County	KE_County_28	

	organisationunitdescription	estimated_number_of_pregnant_women	\
0		NaN	30521.0
1		NaN	12362.0
2		NaN	24517.0
3		NaN	43784.0
4		NaN	18424.0

	population_10_14_year_old_girls	women_of_childbearing_age_(15_49yrs)	\
0		NaN	174354.0
1		NaN	68426.0
2		NaN	225176.0
3		NaN	223505.0
4		NaN	103238.0

	uid_code	uid_year	unnamed:_15	unnamed:_16	\
0	201401_Hsk1YV8kHkT	2014_Hsk1YV8kHkT	NaN	NaN	
1	201401_xuFdFy6t9AH	2014_xuFdFy6t9AH	NaN	NaN	
2	201401_kphDeKC1Fch	2014_kphDeKC1Fch	NaN	NaN	
3	201401_t0J75eHKxz5	2014_t0J75eHKxz5	NaN	NaN	
4	201401_MqnLxQBigG0	2014_MqnLxQBigG0	NaN	NaN	

	unnamed:_17	unnamed:_18	eligible_fp
--	-------------	-------------	-------------

0	NaN	NaN	143833.0
1	NaN	NaN	56064.0
2	NaN	NaN	200659.0
3	NaN	NaN	179721.0
4	NaN	NaN	84814.0

### 3.1.4 4. ke\_fp\_benchmarks\_data.csv

```
[38]: # Make copies of the benchmarks dataframes
df_core_health_workforce1 = df_core_health_workforce.copy()
df_demand_satisfied1 = df_demand_satisfied.copy()
df_mcpr1 = df_mcpr.copy()
df_teenage_pregnancy1 = df_teenage_pregnancy.copy()
df_unmet_need1 = df_unmet_need.copy()
```

```
[39]: # Preview the data
df_core_health_workforce1.head()
df_demand_satisfied1.head()
df_mcpr1.head()
df_teenage_pregnancy1.head()
df_unmet_need1.head()
```

```
[39]: organisationunitname      uid      county_cou \
0      baringo      vvOK1BxTbet      KE_County_30
1      bomet      HMNARUV2CW4      KE_County_36
2      bungoma      KGHhQ5GLd4k      KE_County_39
3      busia      TvflzgVZOK4      KE_County_40
4      elgeyo_marakwet      MqnLxQBigG0      KE_County_28
```

	benchmark_indicator	Total Unmet Need (Married Women, %)	\
0	Total Unmet Need (Married Women, %)	16.6	
1	Total Unmet Need (Married Women, %)	16.7	
2	Total Unmet Need (Married Women, %)	14.6	
3	Total Unmet Need (Married Women, %)	18.6	
4	Total Unmet Need (Married Women, %)	13.5	

	year	source	uid_code
0	2022	KDHS 2022	202201_vvOK1BxTbet
1	2022	KDHS 2022	202201_HMNARUV2CW4
2	2022	KDHS 2022	202201_KGHhQ5GLd4k
3	2022	KDHS 2022	202201_TvflzgVZOK4
4	2022	KDHS 2022	202201_MqnLxQBigG0

## 3.2 b) Initial Feature Engineering

### 3.2.1 CYP computation and grouping

Couple Years of Protection(CYP)-CYP measures the estimated protection provided by FP based on the volume of contraceptive method distribution to clients to help monitor health system performance and track trends and progress over time.

```
[40]: # Define CYP conversion factors
cyp_factors = {
    'condoms': 0.0083,
    'emergency_pill': 0.05,
    'pills_combined_oral_contraceptives': 0.0067,
    'pills_progestin_only_contraceptives': 0.0833,
    'injections': 0.25,
    'implants_1_rod': 2.5,
    'implants_2_rod': 3.8,
    'iucd_hormonal': 4.8,
    'iucd_non_hormonal': 4.6,
    'surgical': 10.0
}

# Initialize total_cyp column
df_service1['total_cyp'] = 0

# Compute total_cyp based on matching column names
for col in df_service1.columns:
    if 'condom' in col:
        df_service1['total_cyp'] += df_service1[col] * cyp_factors['condoms']

    elif 'emergency' in col and 'pill' in col:
        df_service1['total_cyp'] += df_service1[col] *
↪cyp_factors['emergency_pill']

    elif 'combined_oral' in col:
        df_service1['total_cyp'] += df_service1[col] *
↪cyp_factors['pills_combined_oral_contraceptives']

    elif 'progestin_only' in col:
        df_service1['total_cyp'] += df_service1[col] *
↪cyp_factors['pills_progestin_only_contraceptives']

    elif 'injection' in col or 'dmpa' in col:
        df_service1['total_cyp'] += df_service1[col] * cyp_factors['injections']

    elif '1_rod' in col and 'implant' in col:
        df_service1['total_cyp'] += df_service1[col] *
↪cyp_factors['implants_1_rod']
```

```

elif '2_rod' in col and 'implant' in col:
    df_service1['total_cyp'] += df_service1[col] *
↳cyp_factors['implants_2_rod']

elif 'iucd' in col and 'hormonal' in col:
    df_service1['total_cyp'] += df_service1[col] *
↳cyp_factors['iucd_hormonal']

elif 'iucd' in col and 'non_hormonal' in col:
    df_service1['total_cyp'] += df_service1[col] *
↳cyp_factors['iucd_non_hormonal']

elif 'surgical' in col or 'vasectomy' in col or 'btl' in col:
    df_service1['total_cyp'] += df_service1[col] * cyp_factors['surgical']

```

```
[41]: df_service1.head()
```

```

[41]:   year_month country          county      uid  county_code \
0      201404   Kenya  Turkana County kphDeKC1Fch  KE_County_23
1      201404   Kenya   Nandi County t0J75eHKxz5  KE_County_29
2      201404   Kenya West Pokot County XWALbfAPa6n  KE_County_24
3      201404   Kenya   Bomet County HMNARUV2CW4  KE_County_36
4      201404   Kenya  Nairobi County jkG3zaihds  KE_County_47

   estimated_number_of_pregnant_women  fp_attendance_new_clients \
0                                24517                        440
1                                43784                        3572
2                                21198                         745
3                                39762                        2521
4                                158875                       11356

   fp_attendance_re_visits \
0                        896
1                       7044
2                        738
3                       4411
4                       26382

   adolescent_10_14_yrs_receiving_fp_services_new_clients \
0                                0
1                                0
2                                0
3                                0
4                                0

   adolescent_10_14_yrs_receiving_fp_services_re_visits ... \

```



0	0	...
1	0	...
2	0	...
3	0	...
4	0	...

	2020_post_parturm_fp_within_48_hours_new_clients	\
0	0	
1	0	
2	0	
3	0	
4	0	

	2020_post_parturm_fp_within_48_hours_re_visits	\
0	0	
1	0	
2	0	
3	0	
4	0	

	2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion	\
0	0	
1	0	
2	0	
3	0	
4	0	

	2020_voluntary_surgical_contraception_vasectomy_re_insertion	\
0	0	
1	0	
2	0	
3	0	
4	0	

	2020_voluntary_surgical_contraception_btl_ist_time_insertion	\
0	0	
1	0	
2	0	
3	0	
4	0	

	2020_voluntary_surgical_contraception_btl_re_insertion	year	\
0	0	2014	
1	0	2014	
2	0	2014	
3	0	2014	
4	0	2014	

	uid_code	uid_year	total_cyp
0	201404_kphDeKC1Fch	2014_kphDeKC1Fch	41.5945
1	201404_t0J75eHKxz5	2014_t0J75eHKxz5	80.8429
2	201404_XWALbfAPa6n	2014_XWALbfAPa6n	18.7608
3	201404_HMNARUV2CW4	2014_HMNARUV2CW4	18.5713
4	201404_jkG3zaihds	2014_jkG3zaihds	342.4399

[5 rows x 56 columns]

### 3.2.2 FP Method Grouping (New vs Revisits)

```
[42]: # Group FP Methods
df_service1['adolescent_10_24_receiving_fp_new'] = (
    df_service1['adolescent_10_14_yrs_receiving_fp_services_new_clients'] +
    df_service1['adolescent_15_19_yrs_receiving_fp_services_new_clients'] +
    df_service1['adolescent_20_24_yrs_receiving_fp_services_new_clients']
)

df_service1['adolescent_10_24_receiving_fp_revisits'] = (
    df_service1['adolescent_10_14_yrs_receiving_fp_services_re_visits'] +
    df_service1['adolescent_15_19_yrs_receiving_fp_services_re_visits'] +
    df_service1['adolescent_20_24_yrs_receiving_fp_services_re_visits']
)

df_service1['adults_25+_receiving_fp_services_new'] =
    df_service1['2020_adults_25+_receiving_fp_services_new_clients']
df_service1['adults_25+_receiving_fp_services_revisits'] =
    df_service1['2020_adults_25+_receiving_fp_services_re_visits']

df_service1['condoms_new'] =
    df_service1['clients_receiving_female_condoms_new_clients'] +
    df_service1['client_receiving_male_condoms_new_clients']
df_service1['condoms_revisits'] = (
    df_service1['clients_receiving_female_condoms_re_visits'] +
    df_service1['client_receiving_male_condoms_re_visits']
)

df_service1['pills_new'] = (
    df_service1['emergency_contraceptive_pill_new_clients'] +
    df_service1['pills_combined_oral_contraceptive_new_clients'] +
    df_service1['pills_progestin_only_new_clients']
)

df_service1['pills_revisits'] = (
    df_service1['emergency_contraceptive_pill_re_visits'] +
```

```

    df_service1['pills_combined_oral_contraceptive_re_visits'] +
    df_service1['pills_progestin_only_re_visits']
)

df_service1['injectable_new'] = (
    df_service1['2020_fp_injections_dmpa__im_new_clients'] +
    df_service1['2020_fp_injections_dmpa__sc_new_clients']
)

df_service1['injectable_revisits'] = (
    df_service1['2020_fp_injections_dmpa__im_re_visits'] +
    df_service1['2020_fp_injections_dmpa__sc_re_visits']
)

df_service1['implants_new'] = (
    df_service1['2020_implants_insertion_1_rod_ist_time_insertion'] +
    df_service1['2020_implants_insertion_2_rod_ist_time_insertion']
)

df_service1['implants_revisits'] = (
    df_service1['2020_implants_insertion_1_rod_re_insertion'] +
    df_service1['2020_implants_insertion_2_rod_re_insertion']
)

df_service1['iucd_new'] = (
    df_service1['2020_iucd_insertion_hormonal_ist_time_insertion'] +
    df_service1['2020_iucd_insertion_non_hormonal_ist_time_insertion']
)

df_service1['iucd_revisits'] = (
    df_service1['2020_iucd_insertion_hormonal_re_insertion'] +
    df_service1['2020_iucd_insertion_non_hormonal_re_insertion']
)

df_service1['surgical_new'] = (
    ↵
    ↪df_service1['2020_voluntary_surgical_contraception_vasectomy_ist_time_insertion'] ↵
    ↪+
    df_service1['2020_voluntary_surgical_contraception_btl_ist_time_insertion']
)

df_service1['surgical_revisits'] = (
    df_service1['2020_voluntary_surgical_contraception_vasectomy_re_insertion'] ↵
    ↪+
    df_service1['2020_voluntary_surgical_contraception_btl_re_insertion']
)

```

```

df_service1['traditional_new'] = (
    df_service1['2020_clients_given_cycle_beads_new_clients'] +
    df_service1['clients_counselled_natural_family_planning_new_clients']
)

df_service1['traditional_revisits'] = (
    df_service1['2020_clients_given_cycle_beads_re_visits'] +
    df_service1['clients_counselled_natural_family_planning_re_visits']
)

```

```
[43]: df_service1
```

```

[43]:   year_month country          county      uid  county_code \
0      201404   Kenya  Turkana County kphDeKC1Fch KE_County_23
1      201404   Kenya   Nandi County t0J75eHKxz5 KE_County_29
2      201404   Kenya West Pokot County XWALbfAPa6n KE_County_24
3      201404   Kenya   Bomet County HMNARUV2CW4 KE_County_36
4      201404   Kenya Nairobi County jkG3zaihds KE_County_47
...      ...      ...
6199    202409   Kenya  Isiolo County bzOfj0iwdH KE_County_11
6200    202409   Kenya Trans Nzoia County mThvosEflAU KE_County_26
6201    202409   Kenya   Nakuru County ob6SxuRcqU4 KE_County_32
6202    202409   Kenya Tharaka Nithi County T4urHM47nlm KE_County_13
6203    202409   Kenya   Nyeri County ptWVfaCIdVx KE_County_19

      estimated_number_of_pregnant_women  fp_attendance_new_clients \
0                                24517                        440
1                                43784                       3572
2                                21198                        745
3                                39762                       2521
4                               158875                      11356
...                                ...
6199                             7422                        240
6200                             35675                       2805
6201                             78676                      10801
6202                             13004                       1061
6203                             19362                       1516

      fp_attendance_re_visits \
0                                896
1                               7044
2                               738
3                               4411
4                              26382
...                                ...
6199                             683
6200                             7968

```

6201	25114
6202	4490
6203	6719

	adolescent_10_14_yrs_receiving_fp_services_new_clients \
0	0
1	0
2	0
3	0
4	0
...	...
6199	1
6200	1
6201	8
6202	1
6203	5

	adolescent_10_14_yrs_receiving_fp_services_re_visits ... \
0	0 ...
1	0 ...
2	0 ...
3	0 ...
4	0 ...
...	... ...
6199	0 ...
6200	1 ...
6201	5 ...
6202	1 ...
6203	0 ...

	injectable_new	injectable_revisits	implants_new	implants_revisits \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
...	...	...	...	...
6199	171	583	133	84
6200	1164	6236	949	611
6201	3513	13416	4675	1371
6202	644	3420	307	224
6203	539	2622	398	262

	iucd_new	iucd_revisits	surgical_new	surgical_revisits \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0

3	0	0	0	0
4	0	0	0	0
...	...	...	...	...
6199	9	3	1	0
6200	89	17	1	0
6201	533	162	18	0
6202	33	7	0	0
6203	145	59	10	0

	traditional_new	traditional_revisits
0	33	51
1	0	22
2	0	0
3	10	0
4	85	50
...	...	...
6199	129	124
6200	452	131
6201	527	16
6202	254	10
6203	29	0

[6204 rows x 74 columns]

### 3.2.3 FP Method overall banding (pills, condoms, injectables,implants,iucd & surgical)

```
[44]: # Combined method categories
df_service1['condoms'] = df_service1['condoms_new'] +_
    ↪df_service1['condoms_revisits']
df_service1['pills'] = df_service1['pills_new'] + df_service1['pills_revisits']
df_service1['injectables'] = df_service1['injectable_new'] +_
    ↪df_service1['injectable_revisits']
df_service1['implants'] = df_service1['implants_new'] +_
    ↪df_service1['implants_revisits']
df_service1['iucd'] = df_service1['iucd_new'] + df_service1['iucd_revisits']
df_service1['surgical'] = df_service1['surgical_new'] +_
    ↪df_service1['surgical_revisits']

# Compute Total mmodern FP methods
df_service1['total_modern_fp'] = (
    df_service1['condoms'] +
    df_service1['pills'] +
    df_service1['injectables'] +
    df_service1['implants'] +
```

```

    df_service1['iucd'] +
    df_service1['surgical']
)

# Compute Total traditional FP methods
df_service1['traditional'] = df_service1['traditional_new'] +
    df_service1['traditional_revisits']

```

```

[45]: # List of columns to keep
keep_cols = [
    'year_month', 'country', 'county', 'uid', 'uid_code', 'uid_year',
    'county_code',
    'adolescent_10_24_receiving_fp_new',
    'adolescent_10_24_receiving_fp_revisits',
    'adults_25+_receiving_fp_services_new',
    'adults_25+_receiving_fp_services_revisits',
    'condoms_new', 'condoms_revisits', 'traditional_new',
    'pills_new', 'pills_revisits', 'traditional_revisits',
    'injectable_new', 'injectable_revisits', 'traditional',
    'implants_new', 'implants_revisits',
    'iucd_new', 'iucd_revisits',
    'surgical_new', 'surgical_revisits',
    'condoms', 'pills', 'injectables', 'implants', 'iucd', 'surgical',
    'total_modern_fp', 'total_cyp'
]

# Keep only the specified columns
df_service1 = df_service1[keep_cols]

```

## Drop underlying columns

```

[46]: df_service1.columns

```

```

[46]: Index(['year_month', 'country', 'county', 'uid', 'uid_code', 'uid_year',
            'county_code', 'adolescent_10_24_receiving_fp_new',
            'adolescent_10_24_receiving_fp_revisits',
            'adults_25+_receiving_fp_services_new',
            'adults_25+_receiving_fp_services_revisits', 'condoms_new',
            'condoms_revisits', 'traditional_new', 'pills_new', 'pills_revisits',
            'traditional_revisits', 'injectable_new', 'injectable_revisits',
            'traditional', 'implants_new', 'implants_revisits', 'iucd_new',
            'iucd_revisits', 'surgical_new', 'surgical_revisits', 'condoms',
            'pills', 'injectables', 'implants', 'iucd', 'surgical',
            'total_modern_fp', 'total_cyp'],
            dtype='object')

```

### 3.2.4 Joining the datasets

A left join was used to merge the four datasets. The service data was used as the base data. Organisation unit id code (uid\_code) was used to join the four datasets

```
[47]: # Merge df_service1 with df_commodity1
fp_service_comm_df = pd.merge(df_service1, df_commodity1, how='left',
                               on='uid_code')

fp_service_comm_df
```

```
[47]:
```

	year_month_x	country_x	county_x	uid_x	\
0	201404	Kenya	Turkana County	kphDeKC1Fch	
1	201404	Kenya	Nandi County	t0J75eHKxz5	
2	201404	Kenya	West Pokot County	XWALbfAPa6n	
3	201404	Kenya	Bomet County	HMNARUV2CW4	
4	201404	Kenya	Nairobi County	jkG3zaihdSs	
...	...	...	...	...	
6199	202409	Kenya	Isiolo County	bz0fj0iwdDH	
6200	202409	Kenya	Trans Nzoia County	mThvosEflAU	
6201	202409	Kenya	Nakuru County	ob6SxuRcqU4	
6202	202409	Kenya	Tharaka Nithi County	T4urHM47nlm	
6203	202409	Kenya	Nyeri County	ptWVfaCIdVx	

	uid_code	uid_year	county_code_x	\
0	201404_kphDeKC1Fch	2014_kphDeKC1Fch	KE_County_23	
1	201404_t0J75eHKxz5	2014_t0J75eHKxz5	KE_County_29	
2	201404_XWALbfAPa6n	2014_XWALbfAPa6n	KE_County_24	
3	201404_HMNARUV2CW4	2014_HMNARUV2CW4	KE_County_36	
4	201404_jkG3zaihdSs	2014_jkG3zaihdSs	KE_County_47	
...	...	...	...	
6199	202409_bz0fj0iwdDH	2024_bz0fj0iwdDH	KE_County_11	
6200	202409_mThvosEflAU	2024_mThvosEflAU	KE_County_26	
6201	202409_ob6SxuRcqU4	2024_ob6SxuRcqU4	KE_County_32	
6202	202409_T4urHM47nlm	2024_T4urHM47nlm	KE_County_13	
6203	202409_ptWVfaCIdVx	2024_ptWVfaCIdVx	KE_County_19	

	adolescent_10_24_receiving_fp_new	\
0	0	
1	0	
2	0	
3	0	
4	0	
...	...	
6199	159	
6200	1169	
6201	5821	
6202	314	



6203

538

	adolescent_10_24_receiving_fp_revisits \
0	0
1	0
2	0
3	0
4	0
...	...
6199	248
6200	2716
6201	7755
6202	978
6203	907

	adults_25+_receiving_fp_services_new ...	implants_stock_losses \
0	0 ...	0.0
1	0 ...	0.0
2	0 ...	NaN
3	0 ...	0.0
4	0 ...	4.0
...	... ...	...
6199	108 ...	NaN
6200	1209 ...	NaN
6201	3450 ...	NaN
6202	500 ...	NaN
6203	764 ...	NaN

	implants_stock_dispensed	implants_stock_at_hand \
0	2.0	63.0
1	0.0	0.0
2	NaN	NaN
3	0.0	0.0
4	1424.0	20475.0
...	...	...
6199	NaN	NaN
6200	NaN	NaN
6201	NaN	NaN
6202	NaN	NaN
6203	NaN	NaN

	implants_stock_requested	implants_stock_received	iud_stock_losses \
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	NaN	NaN	NaN
3	0.0	0.0	0.0
4	6407.0	20915.0	6.0

...	...	...	...
6199	NaN	NaN	NaN
6200	NaN	NaN	NaN
6201	NaN	NaN	NaN
6202	NaN	NaN	NaN
6203	NaN	NaN	NaN

	iud_stock_dispensed	iud_stock_at_hand	iud_stock_requested \
0	0.0	87.0	0.0
1	0.0	0.0	0.0
2	NaN	NaN	NaN
3	0.0	0.0	0.0
4	660.0	1990.0	6608.0

...	...	...	...
6199	NaN	NaN	NaN
6200	NaN	NaN	NaN
6201	NaN	NaN	NaN
6202	NaN	NaN	NaN
6203	NaN	NaN	NaN

	iud_stock_received
0	0.0
1	0.0
2	NaN
3	0.0
4	236.0

...	...
6199	NaN
6200	NaN
6201	NaN
6202	NaN
6203	NaN

[6204 rows x 81 columns]

```
[48]: # Rename the column
fp_service_comm_df= fp_service_comm_df.rename(columns={"county_code_x": "county_code"})

fp_service_comm_df
```

	year_month_x	country_x	county_x	uid_x \
0	201404	Kenya	Turkana County	kphDeKC1Fch
1	201404	Kenya	Nandi County	t0J75eHKxz5
2	201404	Kenya	West Pokot County	XWALbfAPa6n
3	201404	Kenya	Bomet County	HMNARUV2CW4
4	201404	Kenya	Nairobi County	jkG3zaihdsS

...	...	...	...	...
6199	202409	Kenya	Isiolo County	bz0fj0iwfDH
6200	202409	Kenya	Trans Nzoia County	mThvosEflAU
6201	202409	Kenya	Nakuru County	ob6SxuRcqU4
6202	202409	Kenya	Tharaka Nithi County	T4urHM47nlm
6203	202409	Kenya	Nyeri County	ptWVfaCIvX

	uid_code	uid_year	county_code \
0	201404_kphDeKC1Fch	2014_kphDeKC1Fch	KE_County_23
1	201404_t0J75eHKxz5	2014_t0J75eHKxz5	KE_County_29
2	201404_XWALbfAPa6n	2014_XWALbfAPa6n	KE_County_24
3	201404_HMNARUV2CW4	2014_HMNARUV2CW4	KE_County_36
4	201404_jkG3zaihdsS	2014_jkG3zaihdsS	KE_County_47

...	...	...	...
6199	202409_bz0fj0iwfDH	2024_bz0fj0iwfDH	KE_County_11
6200	202409_mThvosEflAU	2024_mThvosEflAU	KE_County_26
6201	202409_ob6SxuRcqU4	2024_ob6SxuRcqU4	KE_County_32
6202	202409_T4urHM47nlm	2024_T4urHM47nlm	KE_County_13
6203	202409_ptWVfaCIvX	2024_ptWVfaCIvX	KE_County_19

	adolescent_10_24_receiving_fp_new \
0	0
1	0
2	0
3	0
4	0

...	...
6199	159
6200	1169
6201	5821
6202	314
6203	538

	adolescent_10_24_receiving_fp_revisits \
0	0
1	0
2	0
3	0
4	0

...	...
6199	248
6200	2716
6201	7755
6202	978
6203	907

adults\_25+\_receiving\_fp\_services\_new ... implants\_stock\_losses \

0	0	...	0.0
1	0	...	0.0
2	0	...	NaN
3	0	...	0.0
4	0	...	4.0
...	...	...	...
6199	108	...	NaN
6200	1209	...	NaN
6201	3450	...	NaN
6202	500	...	NaN
6203	764	...	NaN

	implants_stock_dispensed	implants_stock_at_hand \
0	2.0	63.0
1	0.0	0.0
2	NaN	NaN
3	0.0	0.0
4	1424.0	20475.0
...	...	...
6199	NaN	NaN
6200	NaN	NaN
6201	NaN	NaN
6202	NaN	NaN
6203	NaN	NaN

	implants_stock_requested	implants_stock_received	iud_stock_losses \
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	NaN	NaN	NaN
3	0.0	0.0	0.0
4	6407.0	20915.0	6.0
...	...	...	...
6199	NaN	NaN	NaN
6200	NaN	NaN	NaN
6201	NaN	NaN	NaN
6202	NaN	NaN	NaN
6203	NaN	NaN	NaN

	iud_stock_dispensed	iud_stock_at_hand	iud_stock_requested \
0	0.0	87.0	0.0
1	0.0	0.0	0.0
2	NaN	NaN	NaN
3	0.0	0.0	0.0
4	660.0	1990.0	6608.0
...	...	...	...
6199	NaN	NaN	NaN
6200	NaN	NaN	NaN

6201	NaN	NaN	NaN
6202	NaN	NaN	NaN
6203	NaN	NaN	NaN

	iud_stock_received
0	0.0
1	0.0
2	NaN
3	0.0
4	236.0
...	...
6199	NaN
6200	NaN
6201	NaN
6202	NaN
6203	NaN

[6204 rows x 81 columns]

```
[49]: # Replace non-finite values (NaN, inf, -inf) with 0
fp_service_comm_df = fp_service_comm_df.replace([np.inf, -np.inf], np.nan).
    ↪ fillna(0)
```

```
[50]: # Convert float columns to int64
df_float_cols = fp_service_comm_df.select_dtypes(include=['float', 'float64']).
    ↪ columns
df_float_cols
```

```
[50]: Index(['total_cyp', 'periodid', 'year_month_y',
            'pills_combined_oral_contraceptive_stock_losses',
            'pills_combined_oral_contraceptive_stock_dispensed',
            'pills_combined_oral_contraceptive_stock_at_hand',
            'pills_combined_oral_contraceptive_stock_requested',
            'pills_combined_oral_contraceptive_stock_received',
            'pills_emergency_pill_stock_losses',
            'pills_emergency_pill_stock_dispensed',
            'pills_emergency_pill_stock_at_hand',
            'pills_emergency_pill_stock_requested',
            'pills_emergency_pill_stock_received',
            'pills_progestin_only_pills_stock_losses',
            'pills_progestin_only_pills_stock_dispensed',
            'pills_progestin_only_pills_stock_at_hand',
            'pills_progestin_only_pills_stock_requested',
            'pills_progestin_only_pills_stock_received',
            'condoms_female_condom_stock_losses',
            'condoms_female_condom_stock_dispensed',
            'condoms_female_condom_stock_at_hand',
```

```

'condoms_female_condom_stock_requested',
'condoms_female_condom_stock_received',
'condoms_male_condom_stock_losses',
'condoms_male_condom_stock_dispensed',
'condoms_male_condom_stock_at_hand',
'condoms_male_condom_stock_requested',
'condoms_male_condom_stock_received', 'injectables_stock_losses',
'injectables_stock_dispensed', 'injectables_stock_at_hand',
'injectables_stock_requested', 'injectables_stock_received',
'implants_stock_losses', 'implants_stock_dispensed',
'implants_stock_at_hand', 'implants_stock_requested',
'implants_stock_received', 'iud_stock_losses', 'iud_stock_dispensed',
'iud_stock_at_hand', 'iud_stock_requested', 'iud_stock_received'],
dtype='object')

```

```
[51]: fp_service_comm_df[df_float_cols] = fp_service_comm_df[df_float_cols].
      ↪astype('int64')
```

```
[52]: fp_service_comm_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 6204 entries, 0 to 6203
```

```
Data columns (total 81 columns):
```

#	Column	Non-Null Count	Dtype
0	year_month_x	6204 non-null	int64
1	country_x	6204 non-null	object
2	county_x	6204 non-null	object
3	uid_x	6204 non-null	object
4	uid_code	6204 non-null	object
5	uid_year	6204 non-null	object
6	county_code	6204 non-null	object
7	adolescent_10_24_receiving_fp_new	6204 non-null	int64
8	adolescent_10_24_receiving_fp_revisits	6204 non-null	int64
9	adults_25+_receiving_fp_services_new	6204 non-null	int64
10	adults_25+_receiving_fp_services_revisits	6204 non-null	int64
11	condoms_new	6204 non-null	int64
12	condoms_revisits	6204 non-null	int64
13	traditional_new	6204 non-null	int64
14	pills_new	6204 non-null	int64
15	pills_revisits	6204 non-null	int64
16	traditional_revisits	6204 non-null	int64
17	injectable_new	6204 non-null	int64
18	injectable_revisits	6204 non-null	int64
19	traditional	6204 non-null	int64
20	implants_new	6204 non-null	int64
21	implants_revisits	6204 non-null	int64

22	iucd_new	6204	non-null	int64
23	iucd_revisits	6204	non-null	int64
24	surgical_new	6204	non-null	int64
25	surgical_revisits	6204	non-null	int64
26	condoms	6204	non-null	int64
27	pills	6204	non-null	int64
28	injectables	6204	non-null	int64
29	implants	6204	non-null	int64
30	iucd	6204	non-null	int64
31	surgical	6204	non-null	int64
32	total_modern_fp	6204	non-null	int64
33	total_cyp	6204	non-null	int64
34	periodid	6204	non-null	int64
35	periodname	6204	non-null	object
36	year_month_y	6204	non-null	int64
37	country_y	6204	non-null	object
38	county_y	6204	non-null	object
39	uid_y	6204	non-null	object
40	county_code_y	6204	non-null	object
41	pills_combined_oral_contraceptive_stock_losses	6204	non-null	int64
42	pills_combined_oral_contraceptive_stock_dispensed	6204	non-null	int64
43	pills_combined_oral_contraceptive_stock_at_hand	6204	non-null	int64
44	pills_combined_oral_contraceptive_stock_requested	6204	non-null	int64
45	pills_combined_oral_contraceptive_stock_received	6204	non-null	int64
46	pills_emergency_pill_stock_losses	6204	non-null	int64
47	pills_emergency_pill_stock_dispensed	6204	non-null	int64
48	pills_emergency_pill_stock_at_hand	6204	non-null	int64
49	pills_emergency_pill_stock_requested	6204	non-null	int64
50	pills_emergency_pill_stock_received	6204	non-null	int64
51	pills_progestin_only_pills_stock_losses	6204	non-null	int64
52	pills_progestin_only_pills_stock_dispensed	6204	non-null	int64
53	pills_progestin_only_pills_stock_at_hand	6204	non-null	int64
54	pills_progestin_only_pills_stock_requested	6204	non-null	int64
55	pills_progestin_only_pills_stock_received	6204	non-null	int64
56	condoms_female_condom_stock_losses	6204	non-null	int64
57	condoms_female_condom_stock_dispensed	6204	non-null	int64
58	condoms_female_condom_stock_at_hand	6204	non-null	int64
59	condoms_female_condom_stock_requested	6204	non-null	int64
60	condoms_female_condom_stock_received	6204	non-null	int64
61	condoms_male_condom_stock_losses	6204	non-null	int64
62	condoms_male_condom_stock_dispensed	6204	non-null	int64
63	condoms_male_condom_stock_at_hand	6204	non-null	int64
64	condoms_male_condom_stock_requested	6204	non-null	int64
65	condoms_male_condom_stock_received	6204	non-null	int64
66	injectables_stock_losses	6204	non-null	int64
67	injectables_stock_dispensed	6204	non-null	int64
68	injectables_stock_at_hand	6204	non-null	int64
69	injectables_stock_requested	6204	non-null	int64

```

70 injectables_stock_received          6204 non-null    int64
71 implants_stock_losses                6204 non-null    int64
72 implants_stock_dispensed             6204 non-null    int64
73 implants_stock_at_hand                6204 non-null    int64
74 implants_stock_requested              6204 non-null    int64
75 implants_stock_received               6204 non-null    int64
76 iud_stock_losses                     6204 non-null    int64
77 iud_stock_dispensed                  6204 non-null    int64
78 iud_stock_at_hand                    6204 non-null    int64
79 iud_stock_requested                  6204 non-null    int64
80 iud_stock_received                   6204 non-null    int64
dtypes: int64(70), object(11)
memory usage: 3.9+ MB

```

```

[53]: # Perform a left merge to retain all rows from fp_service_comm_df
fp_service_comm_pop_df = fp_service_comm_df.merge(
    df_population1[['uid_year', 'eligible_fp']],
    on='uid_year',
    how='left'
)

# Preview the merged DataFrame
fp_service_comm_pop_df.head()

```

```

[53]:   year_month_x  country_x      county_x      uid_x      uid_code \
0      201404      Kenya  Turkana County  kphDeKC1Fch  201404_kphDeKC1Fch
1      201404      Kenya   Nandi County  t0J75eHKxz5  201404_t0J75eHKxz5
2      201404      Kenya West Pokot County  XWALbfAPa6n  201404_XWALbfAPa6n
3      201404      Kenya   Bomet County  HMNARUV2CW4  201404_HMNARUV2CW4
4      201404      Kenya  Nairobi County  jkG3zaihdSs  201404_jkG3zaihdSs

      uid_year  county_code  adolescent_10_24_receiving_fp_new \
0  2014_kphDeKC1Fch  KE_County_23                          0
1  2014_t0J75eHKxz5  KE_County_29                          0
2  2014_XWALbfAPa6n  KE_County_24                          0
3  2014_HMNARUV2CW4  KE_County_36                          0
4  2014_jkG3zaihdSs  KE_County_47                          0

      adolescent_10_24_receiving_fp_revisits \
0                                           0
1                                           0
2                                           0
3                                           0
4                                           0

      adults_25+_receiving_fp_services_new ... implants_stock_dispensed \
0                                           0 ...                          2

```



1		0 ...	0
2		0 ...	0
3		0 ...	0
4		0 ...	1424

	implants_stock_at_hand	implants_stock_requested	implants_stock_received \
0	63	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	20475	6407	20915

	iud_stock_losses	iud_stock_dispensed	iud_stock_at_hand \
0	0	0	87
1	0	0	0
2	0	0	0
3	0	0	0
4	6	660	1990

	iud_stock_requested	iud_stock_received	eligible_fp
0	0	0	200659.0
1	0	0	179721.0
2	0	0	123351.0
3	0	0	198058.0
4	6608	236	822316.0

[5 rows x 82 columns]

```
[54]: # Merge df_core_health_workforce
data_df = fp_service_comm_pop_df.merge(
    df_core_health_workforce[['uid_code',
    ↪ 'core_health_workforce_per_10,000population']],
    on='uid_code', how='left'
)
```

```
[55]: # Merge df_demand_satisfied
data_df = data_df.merge(
    df_demand_satisfied1[['uid_code', 'Demand_Satisfied_by_Modern_Methods_
    ↪ (%)']],
    on='uid_code', how='left'
)
```

```
[56]: # Merge df_mcpr
data_df = data_df.merge(
    df_mcpr1[['uid_code', 'mCPR (Married Women, %)']],
    on='uid_code', how='left'
)
```

```
[57]: # Merge df_teenage_pregnancy
data_df = data_df.merge(
    df_teenage_pregnancy1[['uid_code', 'Teenage Pregnancy Rate (15-19, %)']],
    on='uid_code', how='left'
)
```

```
[58]: # Merge df_unmet_need
data_df = data_df.merge(
    df_unmet_need1[['uid_code', 'Total Unmet Need (Married Women, %)']],
    on='uid_code', how='left'
)
```

```
[59]: # Rename the columns by removing suffixes
data_df.columns = [
    col.replace('_x_x', '')
    .replace('_y_y', '')
    .replace('_x', '')
    .replace('_y', '')
    for col in data_df.columns
]
```

```
[60]: # Preview the data to make sure the columns have been renamed
data_df.head()
```

```
[60]:   year_month  country      county      uid      uid_code \
0      201404   Kenya  Turkana County  kphDeKC1Fch  201404_kphDeKC1Fch
1      201404   Kenya   Nandi County  t0J75eHKxz5  201404_t0J75eHKxz5
2      201404   Kenya West Pokot County  XWALbfAPa6n  201404_XWALbfAPa6n
3      201404   Kenya   Bomet County  HMNARUV2CW4  201404_HMNARUV2CW4
4      201404   Kenya  Nairobi County  jkG3zaihds  201404_jkG3zaihds

      uidear  county_code  adolescent_10_24_receiving_fp_new \
0  2014_kphDeKC1Fch  KE_County_23                        0
1  2014_t0J75eHKxz5  KE_County_29                        0
2  2014_XWALbfAPa6n  KE_County_24                        0
3  2014_HMNARUV2CW4  KE_County_36                        0
4  2014_jkG3zaihds  KE_County_47                        0

      adolescent_10_24_receiving_fp_revisits \
0                        0
1                        0
2                        0
3                        0
4                        0

      adults_25+_receiving_fp_services_new ... iud_stock_dispensed \
0                        0 ...                        0
```

1		0	...	0
2		0	...	0
3		0	...	0
4		0	...	660

	iud_stock_at_hand	iud_stock_requested	iud_stock_received	eligible_fp \
0	87	0	0	200659.0
1	0	0	0	179721.0
2	0	0	0	123351.0
3	0	0	0	198058.0
4	1990	6608	236	822316.0

	core_health_workforce_per_10,000population \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

	Demand_Satisfied_by_Modern_Methods (%)	mCPR (Married Women, %) \
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Teenage Pregnancy Rate (15-19, %)	Total Unmet Need (Married Women, %)
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

[5 rows x 87 columns]

```
[61]: data_df.shape
```

```
[61]: (6204, 87)
```

```
[62]: # Remove duplicate columns
data_df = data_df.loc[:, ~data_df.columns.duplicated()]
```

```
[63]: # Checking the merged data for duplicates
data_df.duplicated().sum()
```

```
[63]: 0
```

```
[64]: # Replace " county" label with blanks in county column

data_df['county'] = data_df['county'].str.replace(' County', '', regex=False)
print(data_df[['county']].head())
```

```

      county
0   Turkana
1     Nandi
2 West Pokot
3     Bomet
4   Nairobi
```

### 3.2.5 Export .csv file for data\_df

```
[65]: #data_df_sorted = data_df.sort_values(by='year_month', ascending=False)

# Export to CSV
#data_df_sorted.to_csv("output/data_df.csv", index=False, encoding='utf-8')
```

### 3.2.6 Composite Calculations

```
[170]: # Calculate total users receiving FP services
data_df['total_users_receiving_fp'] = (
    data_df['adolescent_10_24_receiving_fp_new'] +
    data_df['adolescent_10_24_receiving_fp_revisits'] +
    data_df['adults_25+_receiving_fp_services_new'] +
    data_df['adults_25+_receiving_fp_services_revisits']
)

# Total actual new (Modern fp)
data_df['total_actual_new_modern_fp_methods'] = data_df[['pills_new',
    ↪ 'condoms_new',
    ↪ 'injectable_new',
    ↪ 'implants_new',
    ↪ 'iucd_new',
    ↪ 'surgical_new']].sum(axis=1)

# Total actual revisits (Modern fp)
data_df['total_actual_revisits_modern_fp_methods'] = data_df[['pills_revisits',
    ↪ 'condoms_revisits',
    ↪ 'injectable_revisits',
    ↪ 'implants_revisits', 'iucd_revisits',
```

```

    ↪ 'surgical_revisits']] .sum(axis=1)

# Total actual traditional fp
data_df['total_actual_traditional_methods'] = data_df[['traditional_revisits',
    ↪ 'traditional_revisits']] .sum(axis=1)

# Total actual modern fp
data_df['total_actual_modern_fp'] = (
    data_df['total_actual_new_modern_fp_methods'] +
    data_df['total_actual_revisits_modern_fp_methods']
)

# Total FP (both Modern and Traditional)
data_df['total_fp'] = (data_df['total_actual_modern_fp'] +
    data_df['total_actual_traditional_methods'])

# Proportion adolescents receiving fp
data_df['proportion_adolescents_10_24_yrs_receiving_fp'] = ((
    ↪ data_df['adolescent_10_24_receiving_fp_new'] +
    ↪ data_df['adolescent_10_24_receiving_fp_revisits']) /
    ↪ data_df['total_users_receiving_fp'] )

# Number of months
data_df['number_of_months'] = min(data_df['year_month'].unique(), 12)

# Actual mCPR
data_df['actual_mcpr'] = data_df['total_actual_modern_fp'] /
    ↪ data_df['eligible_fp']

# Actual mCPR monthly
data_df['actual_mcpr_monthly'] = data_df['total_modern_fp'] /
    ↪ (data_df['eligible_fp'] / 12)

# Number of women(10_49_yrs) with unmet need for fp
data_df['number_women_10_49_yrs_with_unmet_need_for_fp'] =
    ↪ data_df['eligible_fp'] - data_df['total_actual_modern_fp']

# Unmet need
data_df['actual_unmet_need_for_modern_fp'] = (
    data_df['number_women_10_49_yrs_with_unmet_need_for_fp'] /
    data_df['eligible_fp']

```

```

)

# Actual core health workers-2013
data_df['actual_core_health_workers_2013_10000_eligible_fp'] =
    ↪(data_df['eligible_fp'] / 10000)

# Actual total demand
data_df['actual_total_demand_for_fp'] = data_df['actual_mcpr'] +
    ↪data_df['actual_unmet_need_for_modern_fp']

# Actual demand satisfied
data_df['actual_demand_satisfied'] = data_df['actual_mcpr'] /
    ↪data_df['actual_total_demand_for_fp']

# Combine pills (COCs + POCs)
data_df['total_pills_dispensed'] = (
    data_df['pills_combined_oral_contraceptive_stock_dispensed'] +
    data_df['pills_progestin_only_pills_stock_dispensed']
)

# Combine condoms (male + female)
data_df['total_condoms_dispensed'] = (
    data_df['condoms_male_condom_stock_dispensed'] +
    data_df['condoms_female_condom_stock_dispensed']
)

# Total all commodities dispensed
data_df['total_commodities_dispensed'] = (
    data_df['total_pills_dispensed'] +
    data_df['total_condoms_dispensed'] +
    data_df['injectables_stock_dispensed'] +
    data_df['implants_stock_dispensed'] +
    data_df['iud_stock_dispensed']
)

# Calculate average monthly commodities dispensed
data_df['average_monthly_commodities_dispensed'] = (
    data_df['total_commodities_dispensed'] / data_df['number_of_months']
)

```

### 3.3 c) Exploratory Data Analysis (EDA)

#### 3.3.1 Descriptive Statistics

##### i) FP service data descriptives

```
[81]: # List of columns to describe
eda_cols = [
    'condoms_new', 'condoms_revisits',
    'pills_new', 'pills_revisits',
    'injectable_new', 'injectable_revisits',
    'implants_new', 'implants_revisits',
    'iucd_new', 'iucd_revisits',
    'surgical_new', 'surgical_revisits'
]

# Basic descriptive statistics
eda_summary = df_service1[eda_cols].describe().T
eda_summary['missing'] = df_service1[eda_cols].isnull().sum()
eda_summary['zeros'] = (df_service1[eda_cols] == 0).sum()
eda_summary['unique'] = df_service1[eda_cols].nunique()
eda_summary['dtype'] = df_service1[eda_cols].dtypes

# Show the summary
print(eda_summary)
```

	count	mean	std	min	25%	50%	\
condoms_new	6204.0	1012.755480	2179.557079	4.0	191.75	483.0	
condoms_revisits	6204.0	502.967924	1201.564246	0.0	43.00	144.0	
pills_new	6204.0	622.910058	860.123122	0.0	183.00	387.0	
pills_revisits	6204.0	909.946325	1276.593789	0.0	178.00	492.5	
injectable_new	6204.0	426.390071	762.405961	0.0	0.00	0.0	
injectable_revisits	6204.0	1470.093649	2597.655200	0.0	0.00	0.0	
implants_new	6204.0	427.715506	881.975366	0.0	0.00	0.0	
implants_revisits	6204.0	187.019987	380.439558	0.0	0.00	0.0	
iucd_new	6204.0	52.249194	137.231216	0.0	0.00	0.0	
iucd_revisits	6204.0	17.744842	50.077124	0.0	0.00	0.0	
surgical_new	6204.0	3.200838	10.788603	0.0	0.00	0.0	
surgical_revisits	6204.0	0.026596	0.460010	0.0	0.00	0.0	

	75%	max	missing	zeros	unique	dtype
condoms_new	1082.00	86502.0	0	0	2194	int64
condoms_revisits	476.25	28442.0	0	176	1501	int64
pills_new	703.00	8793.0	0	1	1639	int64
pills_revisits	1039.25	13292.0	0	3	2186	int64
injectable_new	547.25	5757.0	0	3738	1504	int64
injectable_revisits	2294.00	17377.0	0	3734	2093	int64
implants_new	487.00	11639.0	0	3750	1532	int64
implants_revisits	224.25	4972.0	0	3777	1050	int64
iucd_new	42.00	1343.0	0	3819	486	int64
iucd_revisits	12.00	630.0	0	4050	262	int64
surgical_new	1.00	340.0	0	4594	74	int64
surgical_revisits	0.00	20.0	0	6167	12	int64

```

[82]: # Columns to describe
eda_columns = [
    'year_month', 'country', 'county', 'uid', 'uid_code', 'county_code',
    'adolescent_10_24_receiving_fp_new',
    ↪ 'adolescent_10_24_receiving_fp_revisits',
    'adults_25+_receiving_fp_services_new',
    ↪ 'adults_25+_receiving_fp_services_revisits',
    'condoms_new', 'condoms_revisits',
    'pills_new', 'pills_revisits',
    'injectable_new', 'injectable_revisits',
    'implants_new', 'implants_revisits',
    'iucd_new', 'iucd_revisits',
    'surgical_new', 'surgical_revisits',
    'condoms', 'pills', 'injectables', 'implants', 'iucd', 'surgical',
    'total_modern_fp', 'total_cyp'
]

# Subset the DataFrame
df_eda = df_service1[eda_columns]

# 1. General info
print("=== Basic Info ===")
print(df_eda.info())

# 2. Missing values
print("=== Missing Values ===")
print(df_eda.isnull().sum())

# 3. Descriptive statistics for numeric columns
print("=== Summary Statistics ===")
print(df_eda.describe().T)

# 4. Unique value counts for categorical columns
cat_cols = ['year_month', 'country', 'county', 'uid', 'uid_code', 'county_code']
print("=== Unique Values in Categorical Columns ===")
for col in cat_cols:
    print(f"{col}: {df_eda[col].nunique()} unique values")

# 5. Trends over time (optional)
if pd.api.types.is_datetime64_any_dtype(df_eda['year_month']):
    trend_data = df_eda.groupby('year_month')['total_fp'].sum()
    trend_data.plot(title="Total FP Over Time", figsize=(10, 4))
    plt.ylabel("Total FP")
    plt.xlabel("Month")
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

```



```
# 6. Distribution plots for select variables (optional)
num_vars = ['total_modern_fp', 'total_cyp', 'condoms', 'pills', 'injectables']
for var in num_vars:
    plt.figure(figsize=(6, 3))
    sns.histplot(df_eda[var], bins=30, kde=True)
    plt.title(f'Distribution of {var}')
    plt.tight_layout()
    plt.show()
```

=== Basic Info ===

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 6204 entries, 0 to 6203
```

```
Data columns (total 30 columns):
```

#	Column	Non-Null Count	Dtype
0	year_month	6204 non-null	int64
1	country	6204 non-null	object
2	county	6204 non-null	object
3	uid	6204 non-null	object
4	uid_code	6204 non-null	object
5	county_code	6204 non-null	object
6	adolescent_10_24_receiving_fp_new	6204 non-null	int64
7	adolescent_10_24_receiving_fp_revisits	6204 non-null	int64
8	adults_25+_receiving_fp_services_new	6204 non-null	int64
9	adults_25+_receiving_fp_services_revisits	6204 non-null	int64
10	condoms_new	6204 non-null	int64
11	condoms_revisits	6204 non-null	int64
12	pills_new	6204 non-null	int64
13	pills_revisits	6204 non-null	int64
14	injectable_new	6204 non-null	int64
15	injectable_revisits	6204 non-null	int64
16	implants_new	6204 non-null	int64
17	implants_revisits	6204 non-null	int64
18	iucd_new	6204 non-null	int64
19	iucd_revisits	6204 non-null	int64
20	surgical_new	6204 non-null	int64
21	surgical_revisits	6204 non-null	int64
22	condoms	6204 non-null	int64
23	pills	6204 non-null	int64
24	injectables	6204 non-null	int64
25	implants	6204 non-null	int64
26	iucd	6204 non-null	int64
27	surgical	6204 non-null	int64
28	total_modern_fp	6204 non-null	int64
29	total_cyp	6204 non-null	float64

```
dtypes: float64(1), int64(24), object(5)
```

memory usage: 1.4+ MB

None

=== Missing Values ===

year_month	0
country	0
county	0
uid	0
uid_code	0
county_code	0
adolescent_10_24_receiving_fp_new	0
adolescent_10_24_receiving_fp_revisits	0
adults_25+_receiving_fp_services_new	0
adults_25+_receiving_fp_services_revisits	0
condoms_new	0
condoms_revisits	0
pills_new	0
pills_revisits	0
injectable_new	0
injectable_revisits	0
implants_new	0
implants_revisits	0
iucd_new	0
iucd_revisits	0
surgical_new	0
surgical_revisits	0
condoms	0
pills	0
injectables	0
implants	0
iucd	0
surgical	0
total_modern_fp	0
total_cyp	0

dtype: int64

=== Summary Statistics ===

	count	mean	std \
year_month	6204.0	201906.500000	316.272098
adolescent_10_24_receiving_fp_new	6204.0	951.515796	1235.004562
adolescent_10_24_receiving_fp_revisits	6204.0	1097.991457	1311.978571
adults_25+_receiving_fp_services_new	6204.0	488.387653	987.737741
adults_25+_receiving_fp_services_revisits	6204.0	1466.582366	2959.620140
condoms_new	6204.0	1012.755480	2179.557079
condoms_revisits	6204.0	502.967924	1201.564246
pills_new	6204.0	622.910058	860.123122
pills_revisits	6204.0	909.946325	1276.593789
injectable_new	6204.0	426.390071	762.405961
injectable_revisits	6204.0	1470.093649	2597.655200
implants_new	6204.0	427.715506	881.975366

implants_revisits	6204.0	187.019987	380.439558
iucd_new	6204.0	52.249194	137.231216
iucd_revisits	6204.0	17.744842	50.077124
surgical_new	6204.0	3.200838	10.788603
surgical_revisits	6204.0	0.026596	0.460010
condoms	6204.0	1515.723404	2939.649534
pills	6204.0	1532.856383	2084.882141
injectables	6204.0	1896.483720	3295.194265
implants	6204.0	614.735493	1240.657953
iucd	6204.0	69.994036	184.294491
surgical	6204.0	3.227434	10.830335
total_modern_fp	6204.0	5633.020471	7022.298919
total_cyp	6204.0	2932.328082	5641.835617

	min	25% \
year_month	201401.0000	201609.7500
adolescent_10_24_receiving_fp_new	0.0000	110.0000
adolescent_10_24_receiving_fp_revisits	0.0000	78.0000
adults_25+_receiving_fp_services_new	0.0000	0.0000
adults_25+_receiving_fp_services_revisits	0.0000	0.0000
condoms_new	4.0000	191.7500
condoms_revisits	0.0000	43.0000
pills_new	0.0000	183.0000
pills_revisits	0.0000	178.0000
injectable_new	0.0000	0.0000
injectable_revisits	0.0000	0.0000
implants_new	0.0000	0.0000
implants_revisits	0.0000	0.0000
iucd_new	0.0000	0.0000
iucd_revisits	0.0000	0.0000
surgical_new	0.0000	0.0000
surgical_revisits	0.0000	0.0000
condoms	4.0000	304.0000
pills	2.0000	375.0000
injectables	0.0000	0.0000
implants	0.0000	0.0000
iucd	0.0000	0.0000
surgical	0.0000	0.0000
total_modern_fp	30.0000	1444.0000
total_cyp	0.4704	25.6157

	50%	75% \
year_month	201906.50000	202203.250000
adolescent_10_24_receiving_fp_new	537.00000	1332.000000
adolescent_10_24_receiving_fp_revisits	745.00000	1596.250000
adults_25+_receiving_fp_services_new	0.00000	604.250000
adults_25+_receiving_fp_services_revisits	0.00000	2071.250000
condoms_new	483.00000	1082.000000

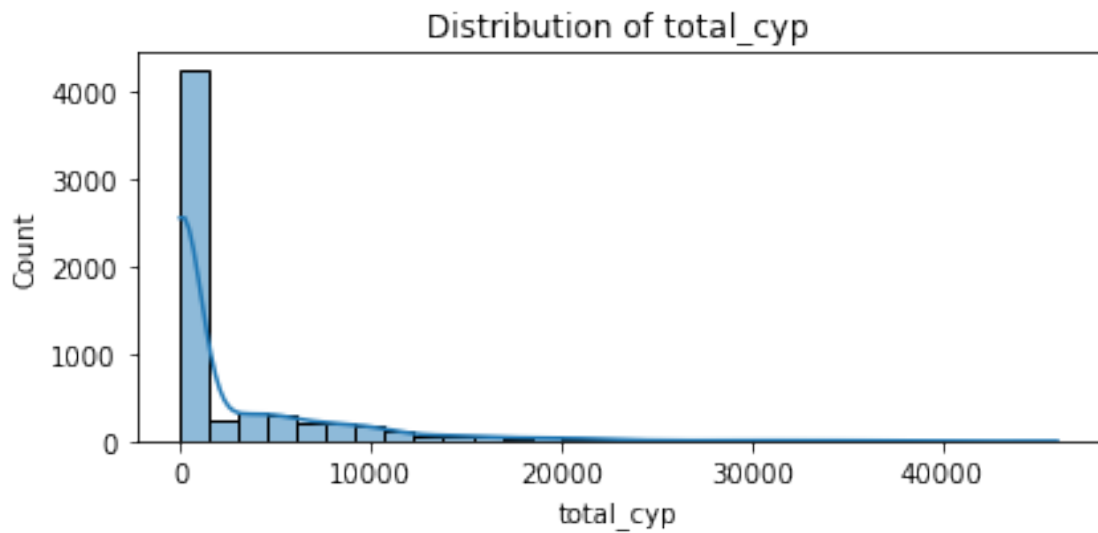
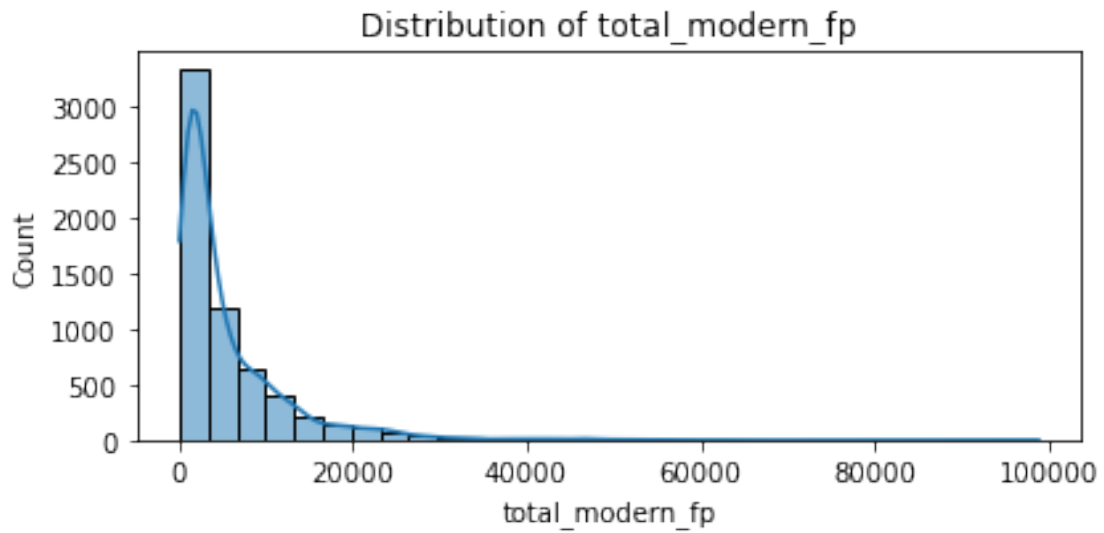
condoms_revisits	144.00000	476.250000
pills_new	387.00000	703.000000
pills_revisits	492.50000	1039.250000
injectable_new	0.00000	547.250000
injectable_revisits	0.00000	2294.000000
implants_new	0.00000	487.000000
implants_revisits	0.00000	224.250000
iucd_new	0.00000	42.000000
iucd_revisits	0.00000	12.000000
surgical_new	0.00000	1.000000
surgical_revisits	0.00000	0.000000
condoms	765.00000	1678.500000
pills	918.00000	1792.000000
injectables	0.00000	2897.500000
implants	0.00000	720.250000
iucd	0.00000	60.000000
surgical	0.00000	1.000000
total_modern_fp	2964.50000	7310.500000
total_cyp	67.22275	3866.048375

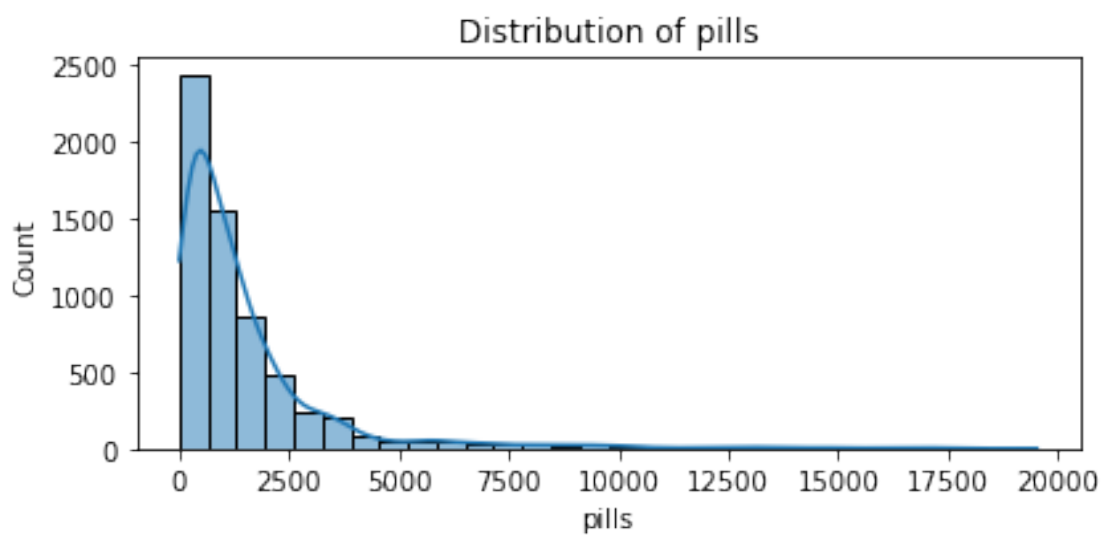
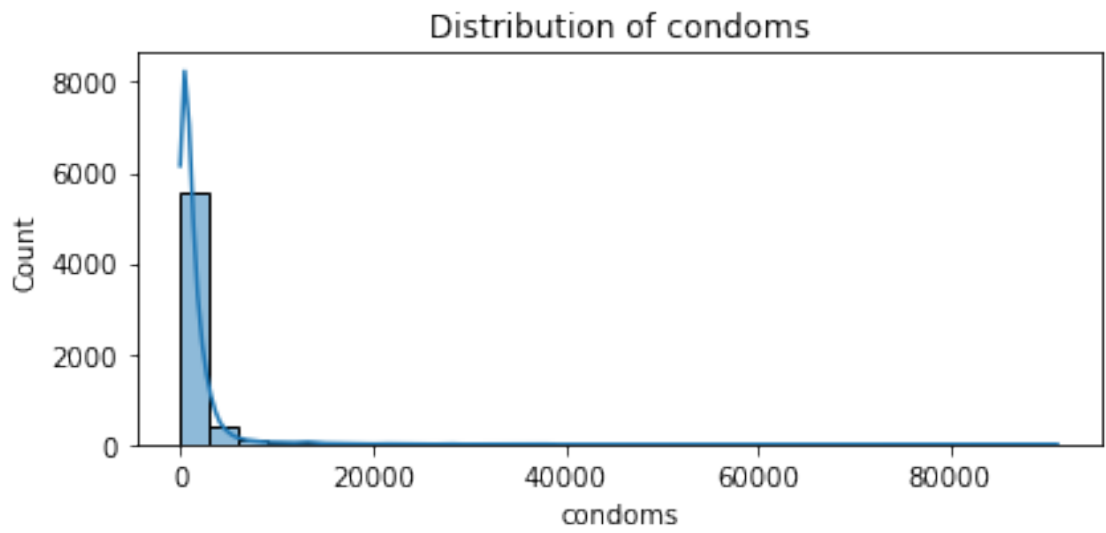
	max
year_month	202412.0000
adolescent_10_24_receiving_fp_new	12244.0000
adolescent_10_24_receiving_fp_revisits	12542.0000
adults_25+_receiving_fp_services_new	8558.0000
adults_25+_receiving_fp_services_revisits	88217.0000
condoms_new	86502.0000
condoms_revisits	28442.0000
pills_new	8793.0000
pills_revisits	13292.0000
injectable_new	5757.0000
injectable_revisits	17377.0000
implants_new	11639.0000
implants_revisits	4972.0000
iucd_new	1343.0000
iucd_revisits	630.0000
surgical_new	340.0000
surgical_revisits	20.0000
condoms	91084.0000
pills	19528.0000
injectables	22859.0000
implants	11838.0000
iucd	1851.0000
surgical	340.0000
total_modern_fp	98876.0000
total_cyp	46015.0367

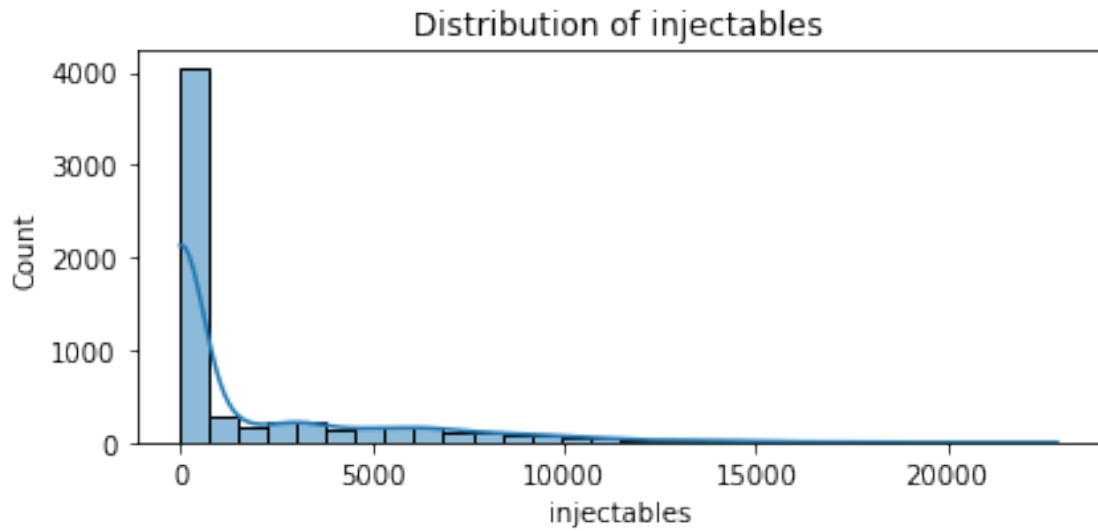
=== Unique Values in Categorical Columns ===

year\_month: 132 unique values

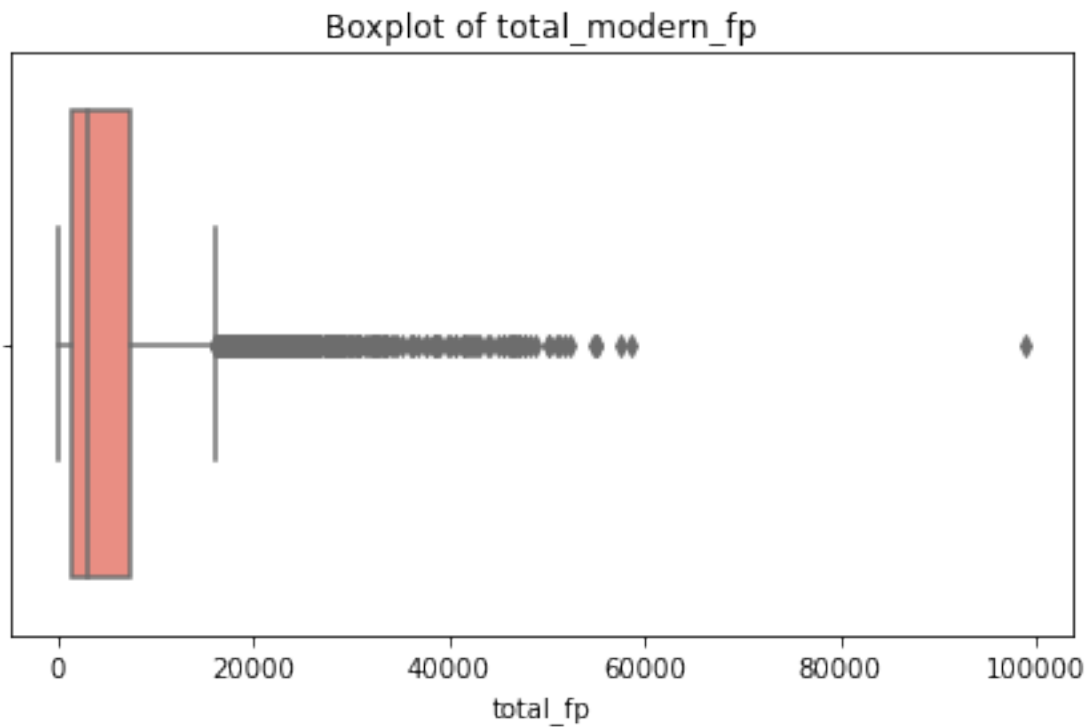
country: 1 unique values  
county: 47 unique values  
uid: 47 unique values  
uid\_code: 6204 unique values  
county\_code: 47 unique values







```
[83]: # Boxplot of total modern fp
plt.figure(figsize=(6,4))
sns.boxplot(x=data_df['total_modern_fp'].dropna(), color='salmon')
plt.title('Boxplot of total_modern_fp') # Set title
plt.xlabel('total_fp') # Set X_label
plt.tight_layout() # Spacing
plt.show()
```



```
[84]: # Convert year_month values into datetime objects
data_df['year_month'] = data_df['year_month'].astype(str) # Convert to string

# Split into year and month
data_df['year'] = data_df['year_month'].str[:4].astype(int)
data_df['month'] = data_df['year_month'].str[4:].astype(int)
```

### 3.3.2 What's the FP method mix composition for the period in focus?

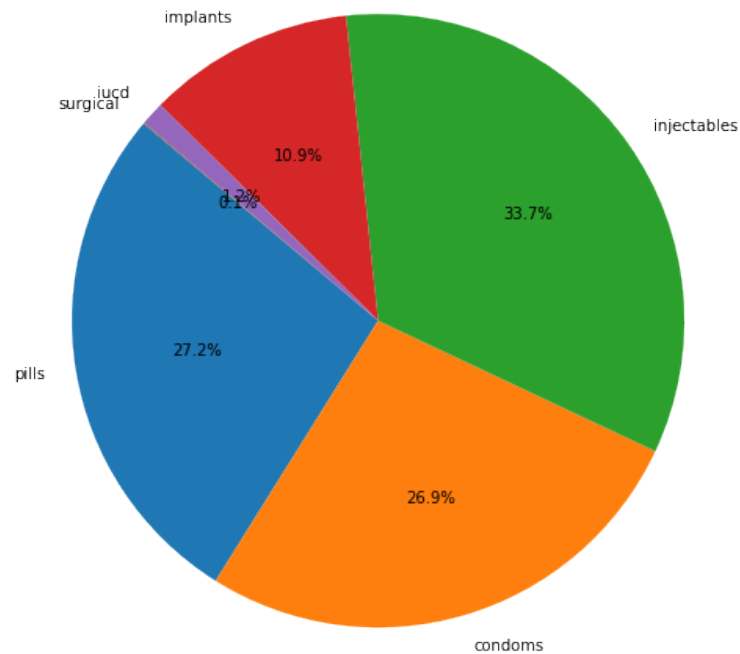
```
[85]: import matplotlib.pyplot as plt
# Group data by year_month and sum the method counts
method_mix = data_df.groupby('year_month')[['pills', 'condoms', 'injectables', 'implants', 'iucd', 'surgical']].sum()

# Calculate the total for each method across the entire period
total_method_counts = method_mix.sum()

# Plotting the pie chart
plt.figure(figsize=(10, 8))
plt.pie(total_method_counts, labels=total_method_counts.index, autopct='%1.1f%%', startangle=140)
plt.title('Majority of the FP methods provided between 2013 and 2024 were short-term methods\n(pills + condoms + injectables ~ 87.2%)', fontsize=16)
plt.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```



Majority of the FP methods provided between 2013 and 2024 were short term methods (pills + condoms + injectables ~ 87.2%)



What's the FP method volume by county?

```
[86]: # Method Mix volume by county

# Sum the total counts for each method by county
county_method_totals = data_df.groupby('county')[['pills', 'condoms',
↪ 'injectables', 'implants', 'iucd', 'surgical']].sum()

# Calculate the total for all methods per county for sorting
county_method_totals['total'] = county_method_totals.sum(axis=1)

# Sort counties by total count in descending order
county_method_totals = county_method_totals.sort_values('total',
↪ ascending=False).drop(columns='total')

# Convert values to thousands and format to 0 decimal places
county_method_totals_thousands = county_method_totals / 1000

# Plotting the stacked bar chart
plt.figure(figsize=(20, 10))
ax = county_method_totals_thousands.plot(kind='bar', stacked=True, figsize=(20,
↪ 10))
```

```

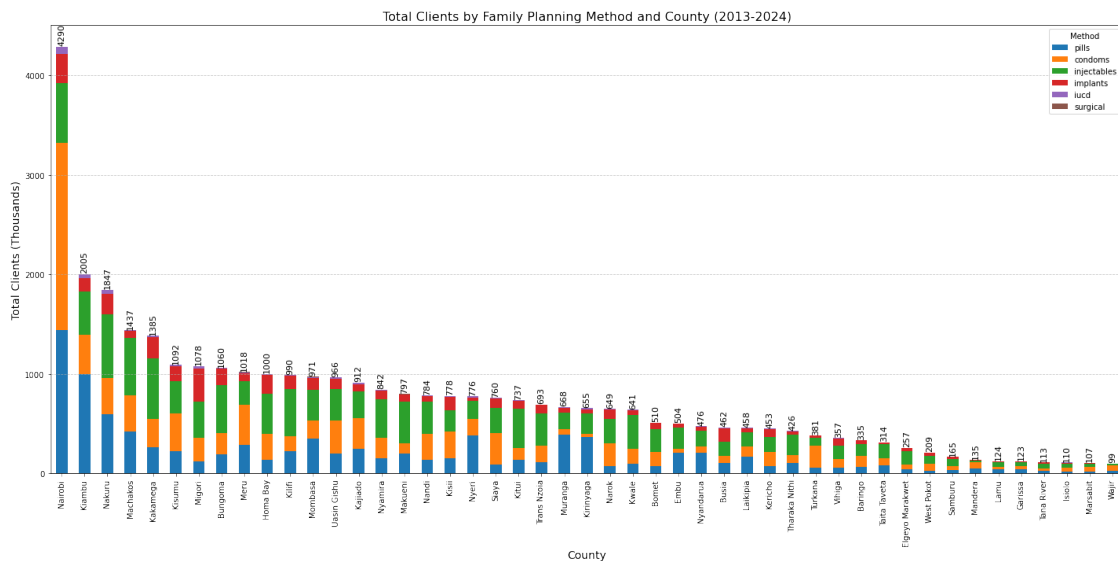
# Add labels and title
plt.xlabel('County', fontsize=14)
plt.ylabel('Total Clients (Thousands)', fontsize=14)
plt.title('Total Clients by Family Planning Method and County (2013-2024)',
↪ fontsize=16)
plt.xticks(rotation=90)
plt.legend(title='Method')
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Add total labels on top of bars
for i, county in enumerate(county_method_totals_thousands.index):
    total_value = county_method_totals_thousands.loc[county].sum()
    # Position the text slightly above the bar. Adjust text position as needed.
    ax.text(i, total_value + 10, f'{total_value:.0f}', ha='center',
↪ va='bottom', rotation=90, fontsize=11)

plt.tight_layout() # Adjust layout to prevent labels overlapping
plt.show()

```

<Figure size 1440x720 with 0 Axes>



### 3.3.3 What are the trends in FP Method uptake over time?

```

[87]: # Plot FP method uptake trends over time

# Group data by year_month and sum the method counts

```

```

method_uptake_time = data_df.groupby('year_month')[['pills', 'condoms', 'injectables', 'implants', 'iucd', 'surgical']].sum()

# Convert values to thousands
method_uptake_time_thousands = method_uptake_time / 1000

# Plotting the stacked bar chart
plt.figure(figsize=(20, 10))
ax = method_uptake_time_thousands.plot(kind='bar', stacked=True, figsize=(20, 10))

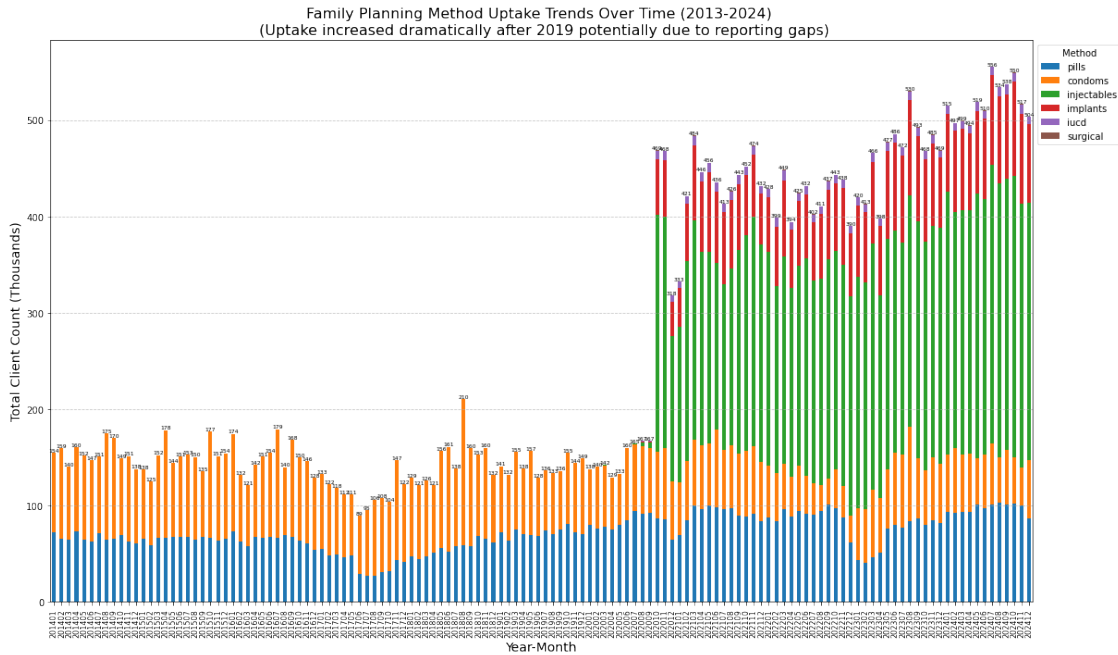
# Add labels and title
plt.xlabel('Year-Month', fontsize=14)
plt.ylabel('Total Client Count (Thousands)', fontsize=14)
plt.title('Family Planning Method Uptake Trends Over Time (2013-2024) \n(Uptake increased dramatically after 2019 potentially due to reporting gaps)', fontsize=16)
plt.xticks(rotation=90, fontsize=8)
plt.legend(title='Method', loc='upper left', bbox_to_anchor=(1, 1))
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Add total labels on top of bars
for i, year_month in enumerate(method_uptake_time_thousands.index):
    total_value = method_uptake_time_thousands.loc[year_month].sum()
    # Position the text slightly above the bar. Adjust text position as needed.
    ax.text(i, total_value, f'{total_value:.0f}', ha='center', va='bottom', fontsize=6)

plt.tight_layout(rect=[0, 0, 0.85, 1]) # Adjust layout to prevent legend overlapping
plt.show()

```

<Figure size 1440x720 with 0 Axes>



### 3.3.4 Total FP Methods vs Women Eligible for FP Over Time

```
[88]: # Plot Total modern FP Methods vs. Women Eligible for FP Over Time

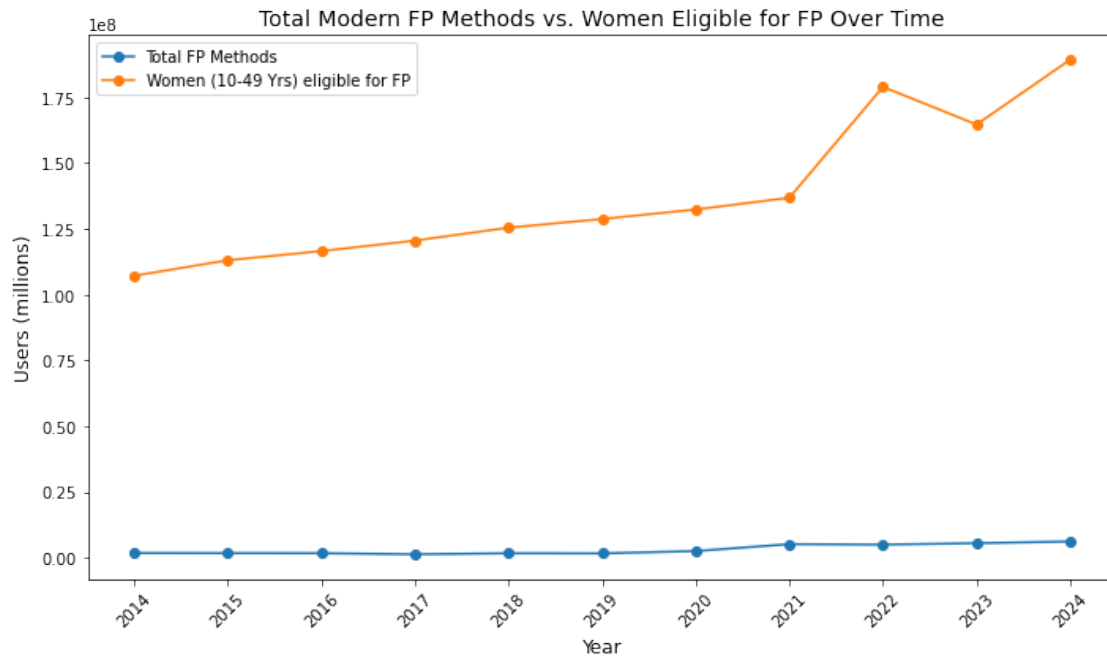
# Group by year and sum 'total_fp', then get the maximum 'eligible_fp' for each
# year
trends = data_df.groupby(data_df['year'])[['total_modern_fp', 'eligible_fp']].
    .agg(
        {'total_modern_fp': 'sum', 'eligible_fp': 'sum'}
    )

# Plotting
plt.figure(figsize=(10, 6))
plt.plot(trends.index, trends['total_modern_fp'], label='Total FP Methods',
    marker='o')
plt.plot(trends.index, trends['eligible_fp'], label='Women (10-49 Yrs) eligible
    for FP', marker='o')

# Add labels and title
plt.xlabel('Year', fontsize=12)
plt.ylabel('Users (millions)', fontsize=12)
plt.title('Total Modern FP Methods vs. Women Eligible for FP Over Time',
    fontsize=14)
plt.xticks(trends.index, rotation=45)
```

```
plt.legend()
plt.grid(False)

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



### 3.3.5 Which FP commodities face the greatest supply-demand mismatch?

```
[89]: # Create month column (Period) for aggregation
if 'date' not in data_df.columns:
    data_df['date'] = pd.to_datetime(data_df['year_month'], format='%Y%m')

# Define the commodity columns we need (issued / stock received)
commodities = {
    'male_condoms': ('condoms_male_condom_stock_dispensed',
    ↪ 'condoms_male_condom_stock_received'),
    'female_condoms': ('condoms_female_condom_stock_dispensed',
    ↪ 'condoms_female_condom_stock_received'),
    'pills': ('pills_combined_oral_contraceptive_stock_dispensed',
    ↪ 'pills_combined_oral_contraceptive_stock_received'),
    'injectables': ('injectables_stock_dispensed',
    ↪ 'injectables_stock_received'),
    'implants': ('implants_stock_dispensed', 'implants_stock_received')
}
```

```

# Make sure the measure columns are numeric
for issued_col, received_col in commodities.values():
    data_df[issued_col] = pd.to_numeric(data_df[issued_col], errors='coerce')
    data_df[received_col] = pd.to_numeric(data_df[received_col],
    ↪errors='coerce')

# Build a tidy dataframe with national-level monthly totals for each commodity
agg_list = []
for name, (issued_col, received_col) in commodities.items():
    monthly = (
        data_df
        .groupby('date')[[issued_col, received_col]]
        .sum()
        .rename(columns={issued_col: 'issued', received_col: 'received'})
    )
    monthly['commodity'] = name
    monthly['coverage_ratio'] = monthly['issued'] / monthly['received'].
    ↪replace(0, pd.NA)
    monthly['stockout_flag'] = monthly['issued'] > monthly['received']
    agg_list.append(monthly.reset_index())

commod_df = pd.concat(agg_list, ignore_index=True)

# Count the number of months where issued exceeded receipts (potential
    ↪stock-out months)
stockouts = commod_df.groupby('commodity')['stockout_flag'].sum().
    ↪reset_index(name='months_with_potential_stockout')
print(stockouts)

# Visualise issued vs received with stock-out shading
sns.set_style('whitegrid')
fig, axes = plt.subplots(len(commodities), 1, figsize=(14, 4 *
    ↪len(commodities)), sharex=True)
for ax, (name, grp) in zip(axes, commod_df.groupby('commodity')):
    ax.plot(grp['date'], grp['issued'], label='Issued', color='steelblue')
    ax.plot(grp['date'], grp['received'], label='Received', color='orange')
    ax.fill_between(grp['date'], grp['issued'], grp['received'],
    ↪where=grp['stockout_flag'], color='red', alpha=0.25, label='Potential
    ↪stock-out')
    ax.set_title(name.replace('_', ' ').title())
    ax.legend()
plt.tight_layout()
plt.show()

```

	commodity	months_with_potential_stockout
0	female_condoms	0

1	implants	82
2	injectables	82
3	male_condoms	0
4	pills	92





### 3.3.6 How well do clients stay on or return for each family planning method once they start, and which methods need the most support to improve continuation?

```
[90]: # New vs revisits columns
methods = {
    'condoms': ('condoms_new', 'condoms_revisits'),
    'pills': ('pills_new', 'pills_revisits'),
    'injectables': ('injectable_new', 'injectable_revisits'),
    'implants': ('implants_new', 'implants_revisits'),
    'iucd': ('iucd_new', 'iucd_revisits')
}

data_df['date'] = pd.to_datetime(data_df['year_month'], format='%Y%m')

for pair in methods.values():
    for col in pair:
        data_df[col] = pd.to_numeric(data_df[col], errors='coerce')

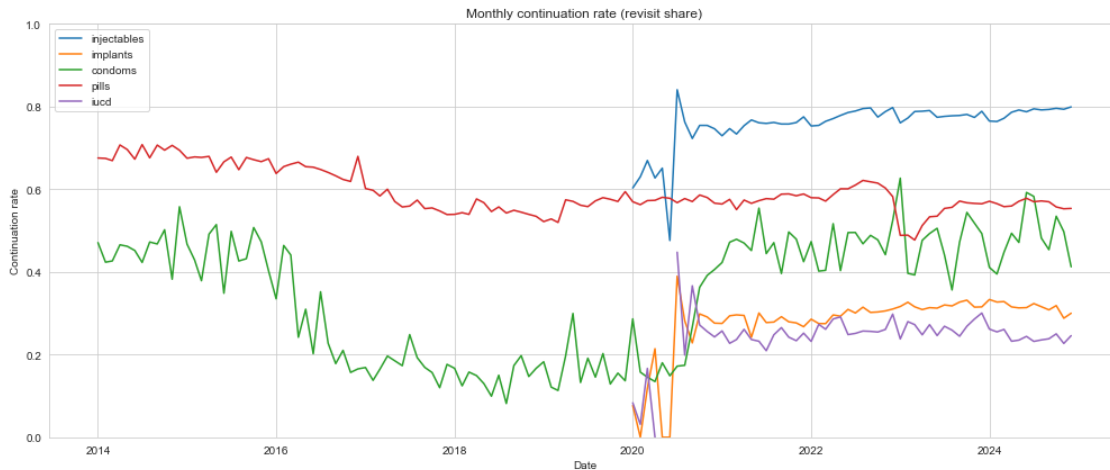
cont_list = []
for name, (new_col, rev_col) in methods.items():
    monthly = data_df.groupby('date')[[new_col, rev_col]].sum().
    ↪rename(columns={new_col: 'new', rev_col: 'revisit'})
    monthly['method'] = name
    monthly['continuation_rate'] = monthly['revisit'] / (monthly['new'] +
    ↪monthly['revisit']).replace(0, pd.NA)
    cont_list.append(monthly.reset_index())

cont_df = pd.concat(cont_list)

# Summary continuation stats
cont_summary = cont_df.groupby('method')['continuation_rate'].
    ↪describe()[['mean', '50%', 'min', 'max']]
print(cont_summary)

# Plot continuation over time for injectables and implants (common methods)
plt.figure(figsize=(14,6))
for method in ['injectables', 'implants', 'condoms', 'pills', 'iucd']:
    subset = cont_df[cont_df['method'] == method]
    plt.plot(subset['date'], subset['continuation_rate'], label=method)
plt.title('Monthly continuation rate (revisit share)')
plt.ylabel('Continuation rate')
plt.xlabel('Date')
plt.ylim(0,1)
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

	mean	50%	min	max
method				
condoms	0.344502	0.402424	0.081719	0.626936
implants	0.283543	0.301429	0.000000	0.500000
injectables	0.749550	0.771955	0.275000	0.840952
iucd	0.245525	0.250819	0.000000	0.447761
pills	0.593910	0.576025	0.477298	0.708238



```
[91]: correlation = data_df['total_users_receiving_fp'] .corr(data_df['total_fp'])
print(f"Correlation between total_users_receiving_fp and total_fp: {correlation:
↪.2f}")
```

Correlation between total\_users\_receiving\_fp and total\_fp: 0.83

### 3.3.7 Proportion of adolescents receiving FP and Adults receiving FP

```
[92]: # Sum totals
adolescents_total = df_service1['adolescent_10_24_receiving_fp_new'].sum()
adults_total = df_service1['adults_25+_receiving_fp_services_new'].sum()
total = adolescents_total + adults_total

# Calculate proportions
adolescents_prop = adolescents_total / total
adults_prop = adults_total / total

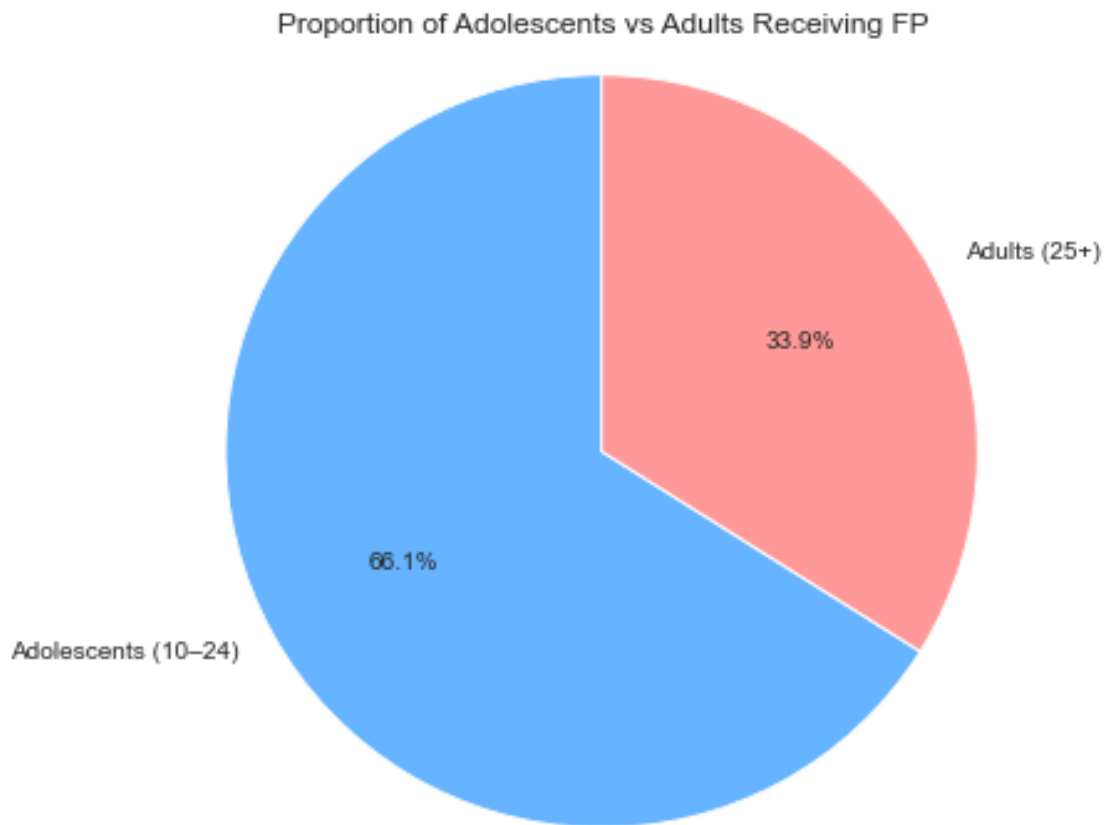
# Display
print(f"Proportion of Adolescents (10-24) receiving FP: {adolescents_prop:.2%}")
print(f"Proportion of Adults (25+) receiving FP: {adults_prop:.2%}")
```

Proportion of Adolescents (10-24) receiving FP: 66.08%

Proportion of Adults (25+) receiving FP: 33.92%

```
[93]: # Data
labels = ['Adolescents (10-24)', 'Adults (25+)']
sizes = [adolescents_total, adults_total]
colors = ['#66b3ff', '#ff9999']

# Plot
plt.figure(figsize=(6, 6))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', colors=colors, startangle=90)
plt.title('Proportion of Adolescents vs Adults Receiving FP')
plt.axis('equal') # Equal aspect ratio ensures the pie is circular.
plt.show()
```



### 3.3.8 Modern Contraceptive Prevalence Rate(mCPR) vs Unmet need

```
[94]: fig = plt.figure(figsize=(20, 16))
fig.suptitle('Analysis of Unmet Need vs Modern Contraceptive Prevalence Rate_
↳(mCPR)', fontsize=20)

mcpr_col = 'mCPR (Married Women, %)'
```

```

unmet_need_col = 'Total Unmet Need (Married Women, %)'
demand_satisfied_col = 'Demand_Satisfied_by_Modern_Methods (%)'

# Filter to rows that have both mCPR and unmet need data
complete_data = data_df.dropna(subset=[mcpr_col, unmet_need_col])
print(f"Number of rows with both mCPR and unmet need data:␣
↪{len(complete_data)}")

# Calculate service statistics-based mCPR
if 'total_modern_fp' in data_df.columns and 'eligible_fp' in data_df.columns:
    data_df['calculated_mcpr'] = (data_df['total_modern_fp'] /␣
↪data_df['eligible_fp']) * 100

# 2. Create county-level summary for comparison
county_summary = data_df.groupby('county').agg({
    'total_modern_fp': 'sum',
    'eligible_fp': 'sum',
    'traditional': 'sum',
    mcpr_col: 'mean',
    unmet_need_col: 'mean',
    demand_satisfied_col: 'mean'
}).reset_index()

# Calculate mCPR at county level based on service statistics
county_summary['calculated_mcpr'] = (county_summary['total_modern_fp'] /␣
↪county_summary['eligible_fp']) * 100

# Filter to counties with complete data
counties_with_data = county_summary.dropna(subset=[mcpr_col, unmet_need_col])
print(f"Number of counties with both mCPR and unmet need data:␣
↪{len(counties_with_data)}")

# Initialize correlation variable
correlation = 0

# If we have counties with both metrics available
if len(counties_with_data) > 0:
    # 3. Scatterplot of mCPR vs Unmet Need
    ax1 = fig.add_subplot(2, 2, 1)
    scatter = sns.scatterplot(
        x=mcpr_col,
        y=unmet_need_col,
        data=counties_with_data,
        s=100,
        ax=ax1
    )

```

```

# Add county labels to points
for i, row in counties_with_data.iterrows():
    ax1.annotate(row['county'],
                  (row[mcpr_col], row[unmet_need_col]),
                  xytext=(5, 5),
                  textcoords='offset points')

# Calculate correlation
correlation = counties_with_data[[mcpr_col, unmet_need_col]].corr().iloc[0, 1]
ax1.set_title(f'Unmet Need vs mCPR by County\nCorrelation: {correlation:.2f}', fontsize=14)
ax1.set_xlabel('mCPR (Married Women, %)', fontsize=12)
ax1.set_ylabel('Total Unmet Need (Married Women, %)', fontsize=12)

# Add regression line
sns.regplot(x=mcpr_col, y=unmet_need_col, data=counties_with_data,
            scatter=False, ax=ax1, color='red')

# 4. Relationship with Demand Satisfied
if demand_satisfied_col in counties_with_data.columns:
    ax2 = fig.add_subplot(2, 2, 2)
    demand_corr = counties_with_data[[mcpr_col, demand_satisfied_col]].corr().iloc[0, 1]

    sns.scatterplot(
        x=mcpr_col,
        y=demand_satisfied_col,
        data=counties_with_data,
        s=100,
        ax=ax2
    )

    # Add regression line
    sns.regplot(x=mcpr_col, y=demand_satisfied_col, data=counties_with_data,
                scatter=False, ax=ax2, color='red')

    ax2.set_title(f'Demand Satisfied vs mCPR\nCorrelation: {demand_corr:.2f}', fontsize=14)
    ax2.set_xlabel('mCPR (Married Women, %)', fontsize=12)
    ax2.set_ylabel('Demand Satisfied by Modern Methods (%)', fontsize=12)

# 5. Compare calculated mCPR with unmet need
counties_with_calculated = county_summary.dropna(subset=[unmet_need_col]).copy()
if len(counties_with_calculated) > 0:
    ax3 = fig.add_subplot(2, 2, 3)
    calculated_corr = np.nan

```

```

# Only calculate correlation if we have enough data points
if len(counties_with_calculated) >= 3:
    calculated_corr = counties_with_calculated[['calculated_mcpr',
↪unmet_need_col]].corr().iloc[0, 1]

sns.scatterplot(
    x='calculated_mcpr',
    y=unmet_need_col,
    data=counties_with_calculated,
    s=100,
    ax=ax3
)

for i, row in counties_with_calculated.iterrows():
    ax3.annotate(row['county'],
                  (row['calculated_mcpr'], row[unmet_need_col]),
                  xytext=(5, 5),
                  textcoords='offset points')

# Add regression line if we have enough data points
if len(counties_with_calculated) >= 3:
    sns.regplot(x='calculated_mcpr', y=unmet_need_col,
↪data=counties_with_calculated,
                  scatter=False, ax=ax3, color='red')

title = f'Unmet Need vs Calculated mCPR\nCorrelation: '
if not np.isnan(calculated_corr):
    title += f"{calculated_corr:.2f}"
else:
    title += "N/A"
ax3.set_title(title, fontsize=14)
ax3.set_xlabel('Calculated mCPR (based on service statistics, %)',
↪fontsize=12)
ax3.set_ylabel('Total Unmet Need (Married Women, %)', fontsize=12)

# 6. Estimate unmet need for counties that have demand satisfied data
ax4 = fig.add_subplot(2, 2, 4)

counties_with_demand = county_summary.dropna(subset=[demand_satisfied_col]).
↪copy()
if len(counties_with_demand) > 0:
    # Estimate unmet need using the formula:
    # Unmet Need = (mCPR / Demand Satisfied) - mCPR
    # Or alternatively: mCPR * ((100 / Demand Satisfied) - 1)
    counties_with_demand['estimated_unmet_need'] =
↪counties_with_demand['calculated_mcpr'] * \

```

```

        ((100 / counties_with_demand[demand_satisfied_col]) - 1)

    # Sort by estimated unmet need
    top_unmet_need = counties_with_demand.sort_values('estimated_unmet_need',
↪ascending=False).head(15)

    # Create bar chart
    sns.barplot(
        x='estimated_unmet_need',
        y='county',
        data=top_unmet_need,
        ax=ax4
    )

    # Add calculated mCPR as text annotations
    for i, row in enumerate(top_unmet_need.itertuples()):
        ax4.text(
            row.estimated_unmet_need + 0.2,
            i,
            f'mCPR: {row.calculated_mcpr:.1f}%',
            va='center'
        )

    ax4.set_title('Top 15 Counties by Estimated Unmet Need', fontsize=14)
    ax4.set_xlabel('Estimated Unmet Need (%)', fontsize=12)
    ax4.set_ylabel('County', fontsize=12)

# Add a textbox with summary findings
text_x = 0.5
text_y = 0.02
summary_text = ("Summary Findings:\n"
    "1. There is a negative correlation between mCPR and unmet need,
↪as expected.\n"
    "2. Counties with lower mCPR tend to have higher unmet need for
↪family planning.\n"
    "3. Service statistics show considerable variation in calculated
↪mCPR across counties.\n"
    "4. Estimated unmet need is highest in counties with very low
↪mCPR values.")

fig.text(text_x, text_y, summary_text, ha='center', va='bottom',
        fontsize=14, bbox=dict(facecolor='white', alpha=0.8))

plt.tight_layout(rect=[0, 0.08, 1, 0.95])

# Output detailed data

```

```

print("\n=== DETAILED RESULTS ===")
print("\nTop 10 counties by unmet need:")
if len(counties_with_data) > 0:
    print(counties_with_data.sort_values(unmet_need_col,
    ↪ascending=False)[['county', mcpr_col, unmet_need_col, demand_satisfied_col]].
    ↪head(10).to_string(index=False))
else:
    print("No counties have both mCPR and unmet need data")

print("\nTop 10 counties by estimated unmet need:")
if len(counties_with_demand) > 0:
    print(counties_with_demand.sort_values('estimated_unmet_need',
    ↪ascending=False)[['county', 'calculated_mcpr', 'estimated_unmet_need']].
    ↪head(10).to_string(index=False))
else:
    print("No counties have data to estimate unmet need")

print("\nCounties with lowest mCPR:")
if len(counties_with_data) > 0:
    print(counties_with_data.sort_values(mcpr_col)[['county', mcpr_col,
    ↪unmet_need_col]].head(10).to_string(index=False))
else:
    print(county_summary.sort_values('calculated_mcpr')[['county',
    ↪'calculated_mcpr']].head(10).to_string(index=False))

print("\nAnalysis complete. See '/workspace/unmet_need_vs_mcpr_analysis.png'
    ↪for visualization.")

```

Number of rows with both mCPR and unmet need data: 47

Number of counties with both mCPR and unmet need data: 47

=== DETAILED RESULTS ===

Top 10 counties by unmet need:

county	mCPR (Married Women, %)	Total Unmet Need (Married Women, %)
Marsabit	4.8	37.6
11.4		
Tana River	22.9	33.6
39.4		
West Pokot	22.6	30.3
42.3		
Samburu	26.5	29.4
42.5		
Siaya	41.6	27.3
59.9		
Isiolo	31.0	27.3



51.5	Kwale	32.5	24.4
57.1	Migori	54.9	20.1
68.3	Mombasa	40.9	19.1
62.0	Busia	56.0	18.6
73.4			

Top 10 counties by estimated unmet need:

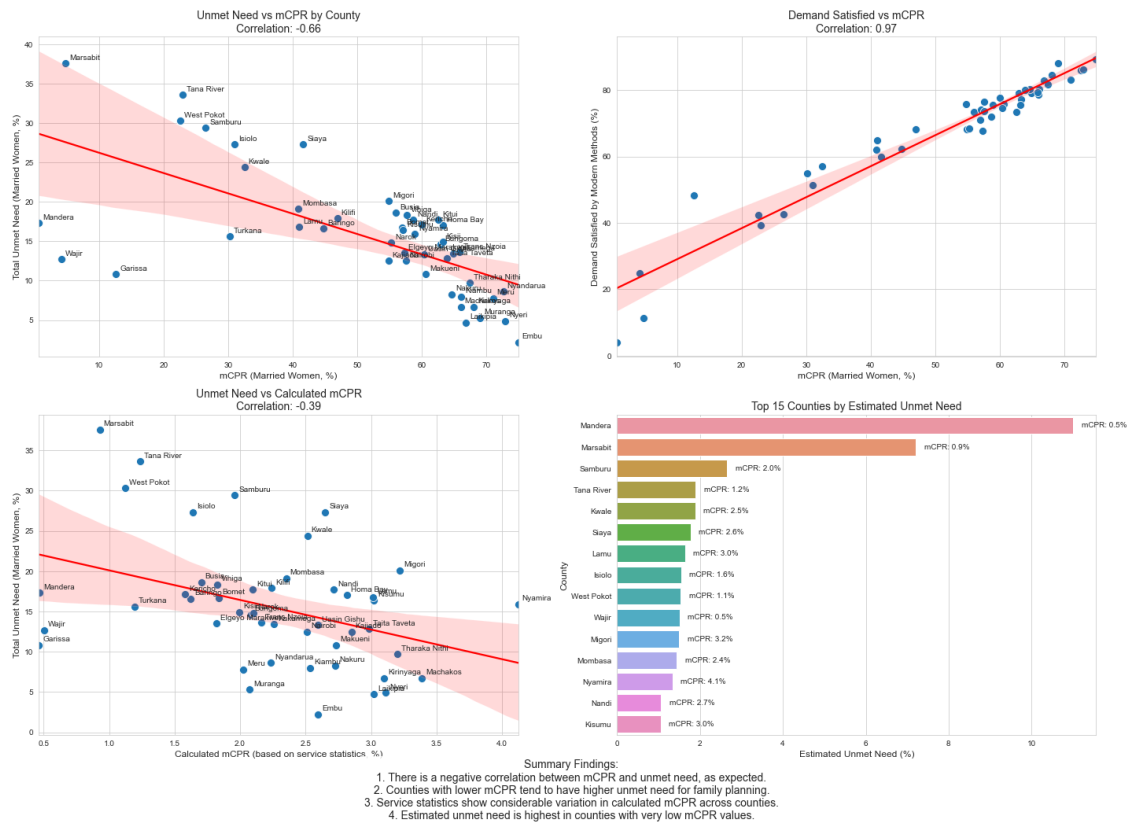
county	calculated_mcpr	estimated_unmet_need
Mandera	0.470532	11.005856
Marsabit	0.928126	7.213332
Samburu	1.958949	2.650342
Tana River	1.235877	1.900867
Kwale	2.513248	1.888237
Siaya	2.648887	1.773295
Lamu	3.013592	1.637013
Isiolo	1.640353	1.544798
West Pokot	1.122974	1.531810
Wajir	0.500968	1.510953

Counties with lowest mCPR:

county	mCPR (Married Women, %)	Total Unmet Need (Married Women, %)
Mandera	0.7	17.3
Wajir	4.2	12.7
Marsabit	4.8	37.6
Garissa	12.6	10.8
West Pokot	22.6	30.3
Tana River	22.9	33.6
Samburu	26.5	29.4
Turkana	30.2	15.6
Isiolo	31.0	27.3
Kwale	32.5	24.4

Analysis complete. See '/workspace/unmet\_need\_vs\_mcpr\_analysis.png' for visualization.

## Analysis of Unmet Need vs Modern Contraceptive Prevalence Rate (mCPR)



## 3.4 d) Modelling

### 3.4.1 Baseline Model\_Linear Regression

```
[187]: # Target and feature columns
target_cols = [
    'total_actual_revisits_modern_fp_methods',
    'total_actual_modern_fp',
    'total_fp',
    'proportion_adolescents_10_24_yrs_receiving_fp',
    'actual_core_health_workers_2013_10000_eligible_fp',
    'average_monthly_commodities_dispensed',
]

feature_cols= feature_cols = ['year', 'year_month', 'county', 'number_of_months']

[188]: X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

```
[190]: # Identify numeric features
categorical_features = X.select_dtypes(include=['object']).columns.tolist()
numeric_features = X.select_dtypes(include=['int64', 'float64']).columns.
    ↪.tolist()

# Define preprocessing steps for numeric data
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),      # Handle missing values
    ('scaler', StandardScaler())                       # Feature scaling
])

# Categorical preprocessing pipeline
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combine transformers
preprocessor = ColumnTransformer(transformers=[
    ('num', numeric_transformer, numeric_features),
    ('cat', categorical_transformer, categorical_features)
])

# Define full pipeline with estimator
model_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', MultiOutputRegressor(LinearRegression()))
])

# Fit the pipeline
model_pipeline.fit(X_train, y_train.fillna(0)) # Fill y_train NaNs with 0 or
    ↪another value if needed

# Predict on test set
y_pred = model_pipeline.predict(X_test)
```

```
[191]: # Evaluate each target separately
for i, column in enumerate(y.columns):
    mse = mean_squared_error(y_test.iloc[:, i], y_pred[:, i])
    r2 = r2_score(y_test.iloc[:, i], y_pred[:, i])
    print(f"{column}:")
    print(f"    MSE = {mse:.2f}")
    print(f"    R² = {r2:.2f}")
    print("-" * 40)
```

total\_actual\_revisits\_modern\_fp\_methods:

```

MSE = 4125334.24
R2 = 0.73
-----
total_actual_modern_fp:
MSE = 11561131.61
R2 = 0.74
-----
total_fp:
MSE = 11615332.03
R2 = 0.74
-----
proportion_adolescents_10_24_yrs_receiving_fp:
MSE = 0.01
R2 = 0.94
-----
actual_core_health_workers_2013_10000_eligible_fp:
MSE = 27.07
R2 = 0.94
-----
average_monthly_commodities_dispensed:
MSE = 77847.34
R2 = 0.24
-----

```

### 3.4.2 XGBoost

```

[199]: # Preprocessing for numeric columns
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

# Preprocessing for categorical columns
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])

# Combine preprocessing
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ]
)

# Full pipeline with XGBoost

```

```

xgb_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', MultiOutputRegressor(XGBRegressor(
        objective='reg:squarederror',
        n_estimators=100,
        learning_rate=0.1,
        max_depth=5,
        random_state=42
    )))
])

# Hyperparameter grid
param_grid = {
    'regressor__estimator__n_estimators': [50, 100],
    'regressor__estimator__learning_rate': [0.05, 0.1],
    'regressor__estimator__max_depth': [3, 5],
    'regressor__estimator__subsample': [0.8, 1.0],
    'regressor__estimator__colsample_bytree': [0.8, 1.0]
}

# Grid search with 3-fold cross-validation
grid_search = GridSearchCV(xgb_pipeline, param_grid, cv=3, scoring='r2',
    verbose=2, n_jobs=-1)

# Fit grid search
grid_search.fit(X_train, y_train)

# Fit model
xgb_pipeline.fit(X_train, y_train)

# Predict
y_pred = xgb_pipeline.predict(X_test)

```

Fitting 3 folds for each of 32 candidates, totalling 96 fits

```

[200]: # Evaluate the model
for i, col in enumerate(target_cols):
    mse = mean_squared_error(y_test[col], y_pred[:, i])
    r2 = r2_score(y_test[col], y_pred[:, i])
    print(f"{col}:\n MSE = {mse:.2f}\n R2 = {r2:.2f}\n" + "-"*40)

```

```

total_actual_revisits_modern_fp_methods:
MSE = 7025875.02
R2 = 0.54

```

```

-----
total_actual_modern_fp:
MSE = 18007509.17

```

```

R2 = 0.59
-----
total_fp:
  MSE = 18141660.95
  R2 = 0.59
-----
proportion_adolescents_10_24_yrs_receiving_fp:
  MSE = 0.06
  R2 = 0.64
-----
actual_core_health_workers_2013_10000_eligible_fp:
  MSE = 44.23
  R2 = 0.89
-----
average_monthly_commodities_dispensed:
  MSE = 82126.79
  R2 = 0.20
-----

```

**Observation** \* XGBoost improved overall performance for some targets but underperformed for others. \* The workforce target remains the most predictable — good sign. \* Commodities dispensed remains poorly predicted

```

[203]: import joblib

# Save model
joblib.dump(XGBRegressor, 'my_model.pkl')

# Load model
model = joblib.load('my_model.pkl')

```