In [ ]:

```
from google.colab import files  # For uploading/downloading files in Colab

# --- Data Handling ---
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# pandas display ALL data
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 200)
```

In [ ]:

```
uploaded = files.upload() # Upload Dataset - Hospital LOS Prediction.csv
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving Dataset - Hospital LOS Prediction.csv to Dataset - Hospital LOS Prediction.csv
```

In [ ]:

```
data1 = pd.read_csv("/content/drive/MyDrive/Dataset/Dataset - Hospital LOS Prediction.csv")
data1
```

Out[ ]:

	Available Extra Rooms in Hospital	Department	Ward_Facility_Code	doctor_name	staff_available	patientid	Age	gender
0	4	gynecology	D	Dr Sophia	0	33070	41-50	Female
1	4	gynecology	B	Dr Sophia	2	34808	31-40	Female
2	2	gynecology	B	Dr Sophia	8	44577	21-30	Female
3	4	gynecology	D	Dr Olivia	7	3695	31-40	Female
4	2	anesthesia	E	Dr Mark	10	108956	71-80	Male
...	...	...	...	...	...	...	...	...
499995	4	gynecology	F	Dr Sarah	2	43001	11-20	Female
499996	13	gynecology	F	Dr Olivia	8	85601	31-40	Female
499997	2	gynecology	B	Dr Sarah	3	22447	11-20	Female
499998	2	radiotherapy	A	Dr John	1	29957	61-70	Female
499999	3	gynecology	F	Dr Sophia	3	45008	41-50	Female

500000 rows × 15 columns

Context:

Hospital management is a vital area that gained a lot of attention during the COVID-19 pandemic. **Inefficient distribution of resources like beds, ventilators might lead to a lot of complications**. However, this can be mitigated by **predicting the length of stay (LOS) of a patient before getting admitted**. Once this is determined, the hospital can plan a suitable treatment, resources, and staff to reduce the LOS and increase the chances of recovery. The rooms and bed can also be planned in accordance with that.

HealthPlus hospital has been incurring a lot of losses in revenue and life due to its inefficient management system. They have been unsuccessful in allocating pieces of equipment, beds, and hospital staff fairly. **A system that could estimate the length of stay (LOS) of a patient can solve this problem to a great extent.**

In [ ]:
```
data1.head()
```

Out[ ]:

	Available Extra Rooms in Hospital	Department	Ward_Facility_Code	doctor_name	staff_available	patientid	Age	gender	T Adm
0	4	gynecology	D	Dr Sophia	0	33070	41-50	Female	T
1	4	gynecology	B	Dr Sophia	2	34808	31-40	Female	T
2	2	gynecology	B	Dr Sophia	8	44577	21-30	Female	T
3	4	gynecology	D	Dr Olivia	7	3695	31-40	Female	U
4	2	anesthesia	E	Dr Mark	10	108956	71-80	Male	T

Data Dictionary:

The data contains various information recorded during the time of admission of the patient. It only contains **records of patients who were admitted to the hospital.** The detailed data dictionary is given below:

- **patientid**: Patient ID
- **Age**: Range of age of the patient
- **gender**: Gender of the patient
- **Type of Admission**: Trauma, emergency or urgent
- **Severity of Illness**: Extreme, moderate, or minor
- **health_condition**s: Any previous health conditions suffered by the patient
- **Visitors with Patient**: The number of patients who accompany the patient
- **Insurance**: Does the patient have health insurance or not?
- **Admission_Deposit**: The deposit paid by the patient during admission
- **Stay (in days)**: The number of days that the patient has stayed in the hospital. This is the **target variable**
- **Available Extra Rooms in Hospital**: The number of rooms available during admission
- **Department**: The department which will be treating the patient
- **Ward_Facility_Code**: The code of the ward facility in which the patient will be admitted
- **doctor_name**: The doctor who will be treating the patient
- **staff_available**: The number of staff who are not occupied at the moment in the ward

Objective:

As a Data Scientist, you have been hired by HealthPlus to analyze the data, find out **what factors affect the LOS the most, and come up with a machine learning model which can predict the LOS of a patient** using the data available during admission and after running a few tests. Also, **bring about useful insights and policies from the data, which can help the hospital to improve their health care infrastructure and revenue.**

```
In [ ]: # EDA
        data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500000 entries, 0 to 499999
Data columns (total 15 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   Available Extra Rooms in Hospital  500000 non-null  int64  
 1   Department                         500000 non-null  object 
 2   Ward_Facility_Code                 500000 non-null  object 
 3   doctor_name                        500000 non-null  object 
 4   staff_available                    500000 non-null  int64  
 5   patientid                          500000 non-null  int64  
 6   Age                                500000 non-null  object 
 7   gender                             500000 non-null  object 
 8   Type of Admission                  500000 non-null  object 
 9   Severity of Illness                500000 non-null  object 
 10  health_conditions                  348112 non-null  object 
 11  Visitors with Patient              500000 non-null  int64  
 12  Insurance                          500000 non-null  object 
 13  Admission_Deposit                  500000 non-null  float64
 14  Stay (in days)                     500000 non-null  int64  
dtypes: float64(1), int64(5), object(9)
memory usage: 57.2+ MB
```

health_conditions is the only column with missing values (about ~150k rows). Impute as "Unknown/None"

```
In [ ]: data1['health_conditions'] = data1['health_conditions'].fillna('Unknown')
```

```
In [ ]: data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500000 entries, 0 to 499999
Data columns (total 15 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   Available Extra Rooms in Hospital  500000 non-null  int64  
 1   Department                         500000 non-null  object 
 2   Ward_Facility_Code                 500000 non-null  object 
 3   doctor_name                        500000 non-null  object 
 4   staff_available                    500000 non-null  int64  
 5   patientid                          500000 non-null  int64  
 6   Age                                500000 non-null  object 
 7   gender                             500000 non-null  object 
 8   Type of Admission                  500000 non-null  object 
 9   Severity of Illness                500000 non-null  object 
 10  health_conditions                  500000 non-null  object 
 11  Visitors with Patient              500000 non-null  int64  
 12  Insurance                          500000 non-null  object 
 13  Admission_Deposit                  500000 non-null  float64
 14  Stay (in days)                     500000 non-null  int64  
dtypes: float64(1), int64(5), object(9)
memory usage: 57.2+ MB
```

In [ ]:
```
# Check for duplicates
data1.duplicated().sum() # Check for zero duplicates
```

Out[ ]:
```
np.int64(0)
```

In [ ]:
```
# Continuous Variables
data1.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	
Available Extra Rooms in Hospital	500000.0	3.638800	2.698124	0.000000	2.000000	3.000000	
staff_available	500000.0	5.020470	3.158103	0.000000	2.000000	5.000000	
patientid	500000.0	63150.519058	41689.479956	-3269.000000	25442.000000	57864.000000	10333
Visitors with Patient	500000.0	3.549414	2.241054	0.000000	2.000000	3.000000	
Admission_Deposit	500000.0	4722.315734	1047.324220	1654.005148	4071.714532	4627.003792	50
Stay (in days)	500000.0	12.381062	7.913174	3.000000	8.000000	9.000000	

Available Extra Rooms in Hospital: Range is 0-24. Makes sense. Capacity is affected by LOS. Avoid Getting 0 available rooms. On avg, 3.6 rooms are available

Staff Available: Range 0-10. Avoid having 0 staff available. pateint ID: Ignore / Drop eventually??? On avg = 5

Visitors with Patient: 0-32. Doesnt affect LOS? Drop? Avoid Outliers

Admission Deposit: 1047-10104. This range is large. Maybe severity correlates with Deposit. Maybe connected to LOS?

Stay (in days): Target variable (y) !!!

In [ ]:
```
cat_col = data1.select_dtypes(include='object').columns # Get categorical columns
print("Catagorical Columns:",cat_col,"\n") # Print cat cols

print("\nRelative frequencies for each category:")

# Loop through categorical columns and get proportions
for column in cat_col:
  print(data1[column].value_counts(normalize=True)) # Normalized vals
  print("-"*50)

plt.figure(figsize=(8,6))

# Visualize proportions for easy readibility
#for column in cat_col:
    #plt.figure(figsize=(8,6))
    #data1[column].value_counts(normalize=True).plot(kind='bar')
    #plt.title(f"Proportions of {column}")
    #plt.ylabel("Proportion")
    #plt.xlabel(column)
    #plt.show()
```

```
Catagorical Columns: Index(['Department', 'Ward_Facility_Code', 'doctor_name', 'Age', 'gender',
       'Type of Admission', 'Severity of Illness', 'health_conditions',
       'Insurance'],
      dtype='object')


Relative frequencies for each category:
Department
gynecology            0.686956
radiotherapy          0.168630
anesthesia            0.088358
TB & Chest disease    0.045780
surgery               0.010276
Name: proportion, dtype: float64
--------------------------------------------------
Ward_Facility_Code
F    0.241076
D    0.238110
B    0.207770
E    0.190748
A    0.093102
C    0.029194
Name: proportion, dtype: float64
--------------------------------------------------
doctor_name
Dr Sarah     0.199192
Dr Olivia    0.196704
Dr Sophia    0.149506
Dr Nathan    0.141554
Dr Sam       0.111422
Dr John      0.102526
Dr Mark      0.088820
Dr Isaac     0.006718
Dr Simon     0.003558
Name: proportion, dtype: float64
--------------------------------------------------
Age
21-30     0.319586
31-40     0.266746
41-50     0.160812
11-20     0.093072
61-70     0.053112
51-60     0.043436
71-80     0.037406
81-90     0.016362
0-10      0.006736
91-100    0.002732
Name: proportion, dtype: float64
--------------------------------------------------
gender
Female    0.74162
Male      0.20696
Other     0.05142
Name: proportion, dtype: float64
--------------------------------------------------
Type of Admission
Trauma       0.621072
Emergency    0.271568
Urgent       0.107360
```

```
Name: proportion, dtype: float64
--------------------------------------------------
Severity of Illness
Moderate    0.560394
Minor       0.263074
Extreme     0.176532
Name: proportion, dtype: float64
--------------------------------------------------
health_conditions
Unknown               0.303776
Other                 0.188822
High Blood Pressure   0.158804
Diabetes              0.147288
Asthama               0.131028
Heart disease         0.070282
Name: proportion, dtype: float64
--------------------------------------------------
Insurance
Yes    0.78592
No     0.21408
Name: proportion, dtype: float64
--------------------------------------------------
```

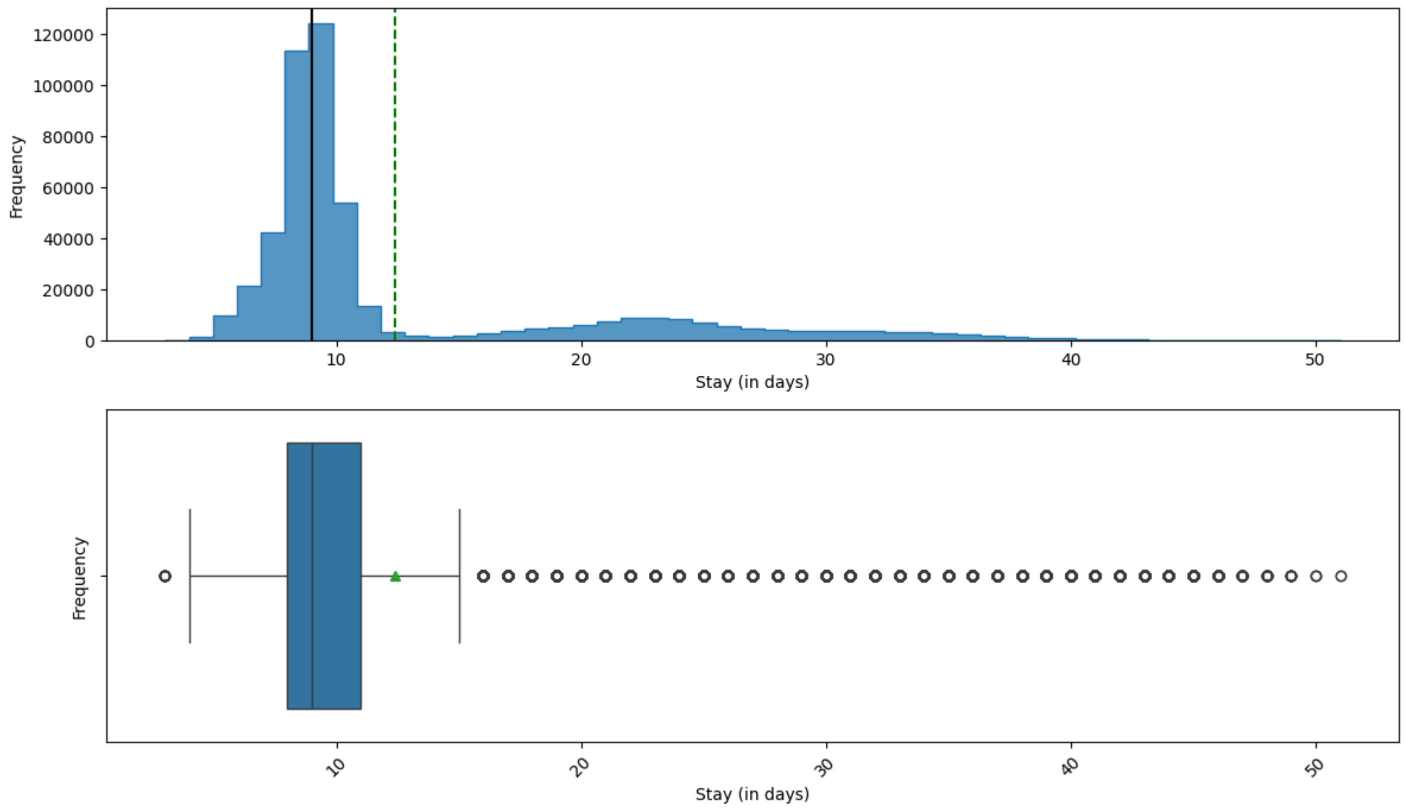
Out[ ]:
```
<Figure size 800x600 with 0 Axes>
<Figure size 800x600 with 0 Axes>
```

In [ ]:
```
#@title Univariate Analysis Functions
def histogram_boxplot(data, feature, figsize=(12, 7), kde=False, bins=None):
    """
    Boxplot and histogram combined

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (12,7))
    kde: whether to show the density curve (default False)
    bins: number
    """
    if bins == None:
        bins = len(data[feature].unique())
        print("Num Bins:",bins)
    figure, (ax1, ax2) = plt.subplots(nrows=2, ncols=1, figsize=figsize) # returns a tuple of 2 
    # Make Histogram
    sns.histplot(data=data, x=feature, kde=kde, element="step", ax=ax1, bins=bins)
    ax1.set_xlabel(feature)
    ax1.set_ylabel("Frequency")
    ax1.axvline(data[feature].mean(), color='green', linestyle='--')
    ax1.axvline(data[feature].median(), color='k', linestyle='-')
    # Make Boxplot
    sns.boxplot(data=data, x=feature, ax=ax2, showmeans= True)
    ax2.set_xticklabels(ax2.get_xticklabels(), rotation=45)
    ax2.set_xlabel(feature)
    ax2.set_ylabel("Frequency")
    figure.tight_layout()
    plt.show()
    print("ax1: mean:", data[feature].mean(), "\t ax2 median:", data[feature].median())
    print("ax2: mean:",  data[feature].mean(), "\t ax2 median:", data[feature].median())
    print("-"*50)
    return
```

```python
# Call function
histogram_boxplot(data1, "Stay (in days)", kde= False) # We want to predict this
```

```
Num Bins: 49
```

```
/tmp/ipython-input-3439198344.py:24: UserWarning: set_ticklabels() should only be used with a fix
ed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax2.set_xticklabels(ax2.get_xticklabels(), rotation=45)
```




```
ax1: mean: 12.381062     ax2 median: 9.0
ax2: mean: 12.381062     ax2 median: 9.0
--------------------------------------------------
```

I notice the right skew of patient's length of stay. This tail portion of the distribution is what I should want to focus on being able to proedict with accuracy

In [ ]:

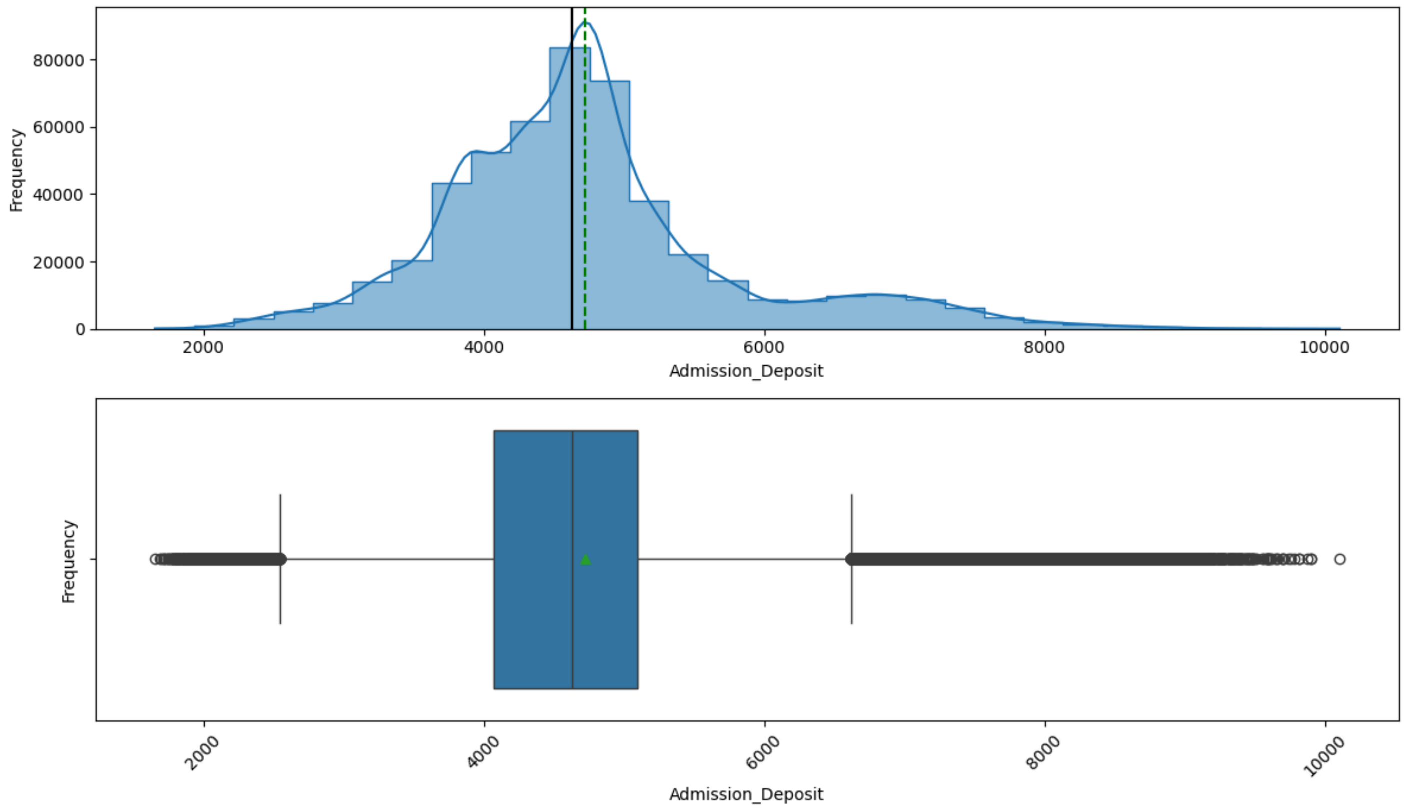
```python
# Get continuous variable from my dataset
cont_cols = data1.select_dtypes(include='number').columns
print("Continuous Columns:",cont_cols,"\n")
```

```
Continuous Columns: Index(['Available Extra Rooms in Hospital', 'staff_available', 'patientid',
       'Visitors with Patient', 'Admission_Deposit', 'Stay (in days)'],
      dtype='object')
```

In [ ]:

```python
histogram_boxplot(data1, 'Admission_Deposit', kde=True, bins = 30)
```

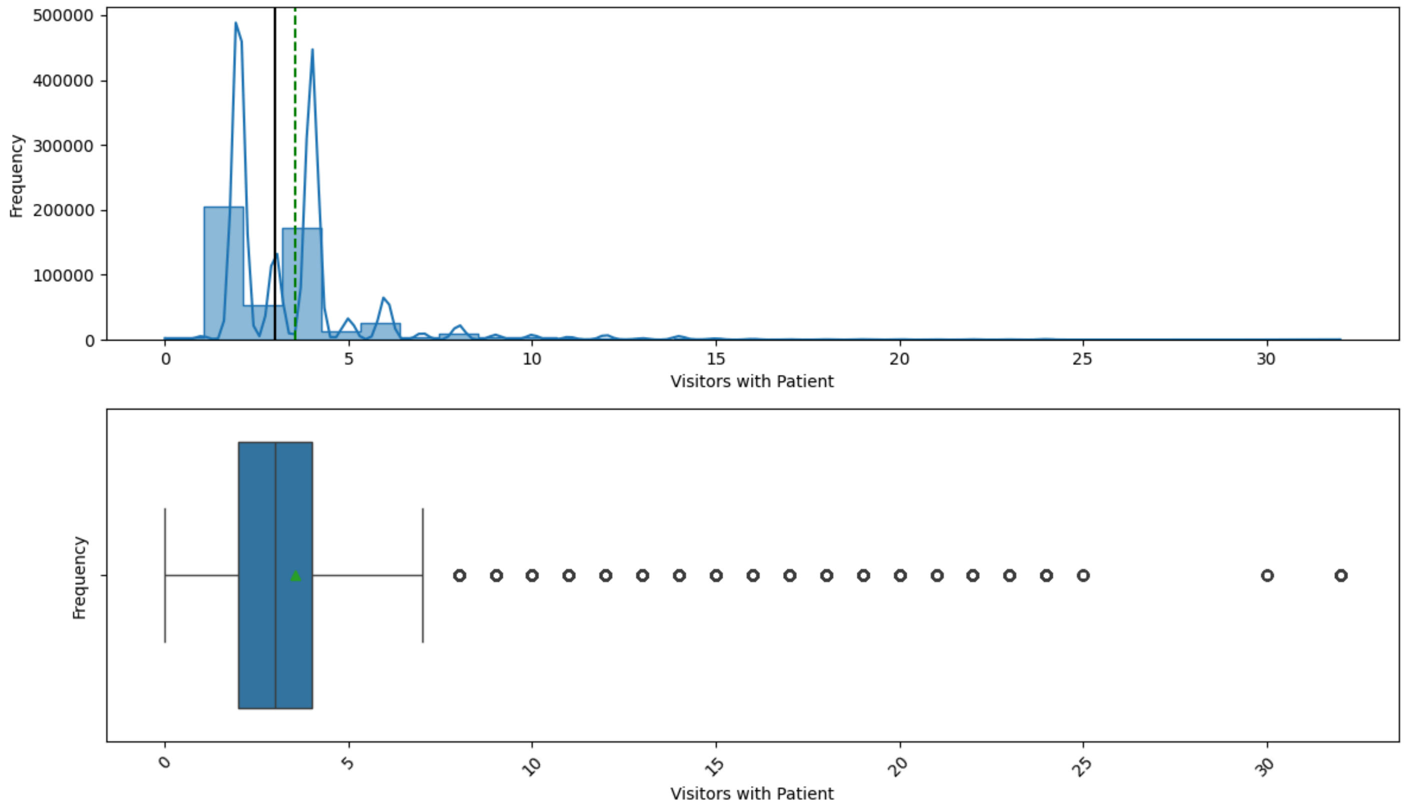
```
/tmp/ipython-input-3439198344.py:24: UserWarning: set_ticklabels() should only be used with a fix
ed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax2.set_xticklabels(ax2.get_xticklabels(), rotation=45)
```




```
ax1: mean: 4722.3157339630625    ax2 median: 4627.0037919999995
ax2: mean: 4722.3157339630625    ax2 median: 4627.0037919999995
--------------------------------------------------
```

In [ ]:
```
# Lets look at the number of visitors per Doctor

i = data1.groupby('doctor_name')['Visitors with Patient'].sum().sort_values(ascending=True)
histogram_boxplot(data1, 'Visitors with Patient', kde=True, bins = 30)
i
```

```
/tmp/ipython-input-3439198344.py:24: UserWarning: set_ticklabels() should only be used with a fix
ed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax2.set_xticklabels(ax2.get_xticklabels(), rotation=45)
```




```
ax1: mean: 3.549414      ax2 median: 3.0
ax2: mean: 3.549414      ax2 median: 3.0
--------------------------------------------------
```

Out[ ]:

doctor_name	Visitors with Patient
Dr Simon	6004
Dr Isaac	11485
Dr Mark	171933
Dr John	192439
Dr Sam	204262
Dr Nathan	245902
Dr Sophia	258256
Dr Olivia	341773
Dr Sarah	342653

dtype: int64

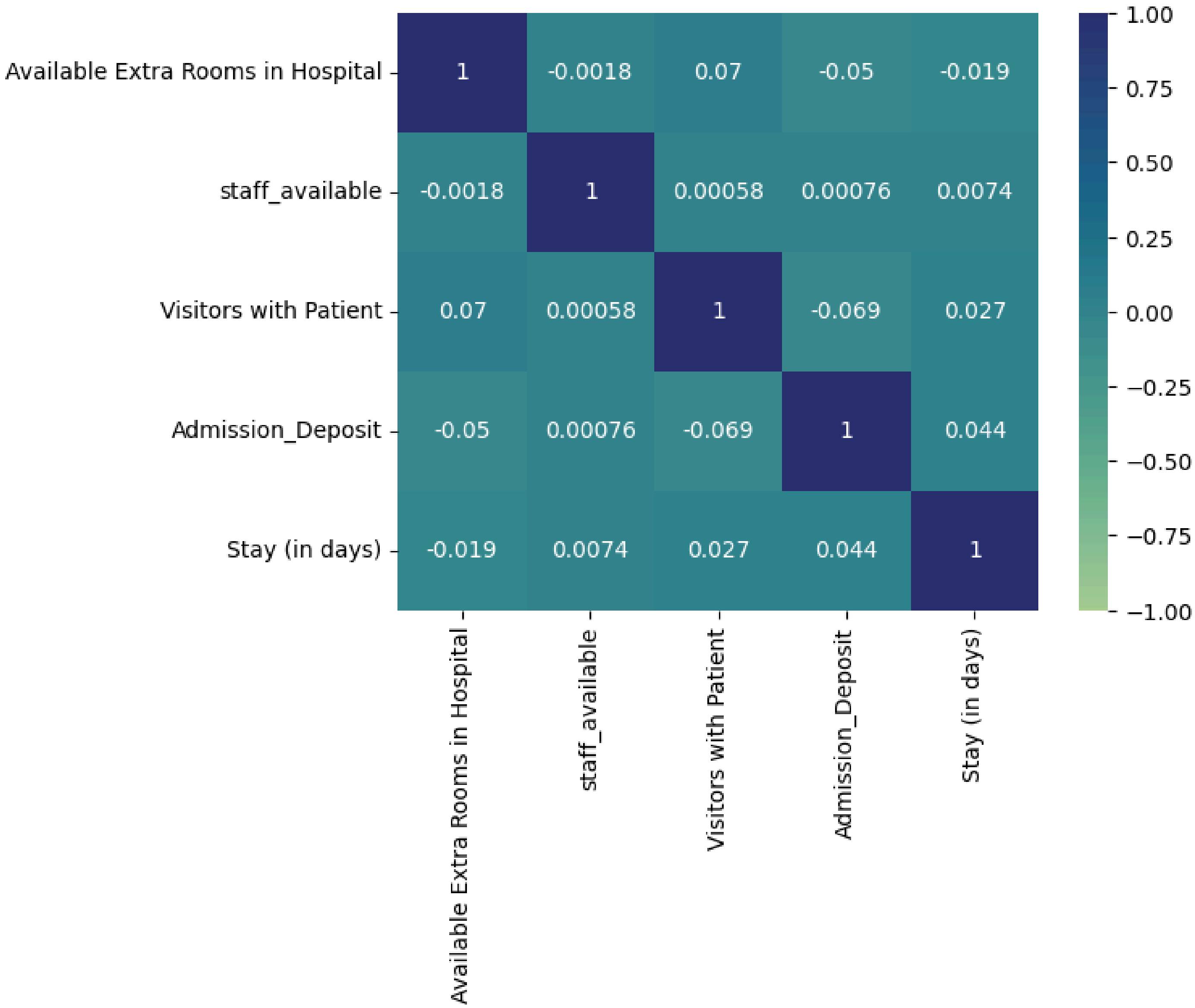
In [ ]:

```
#@title Bivariate Analysis Numeric
num_data = data1.select_dtypes(include='number') # Grabs numeric data from data1
print("Numeric Columns:",num_data.columns,"\n") # Grabs column names of those numeric data

# Drop redundant patient id
num_data = num_data.drop('patientid', axis=1) # drop row

num_data.corr() # correlation calculation among numeric features
```

```
# Make heatmaps
sns.heatmap(num_data.corr(), annot=True, cmap='crest', vmax=1, vmin = -1)
```

```
Numeric Columns: Index(['Available Extra Rooms in Hospital', 'staff_available', 'patientid',
       'Visitors with Patient', 'Admission_Deposit', 'Stay (in days)'],
      dtype='object')
```

Out[ ]: <Axes: >

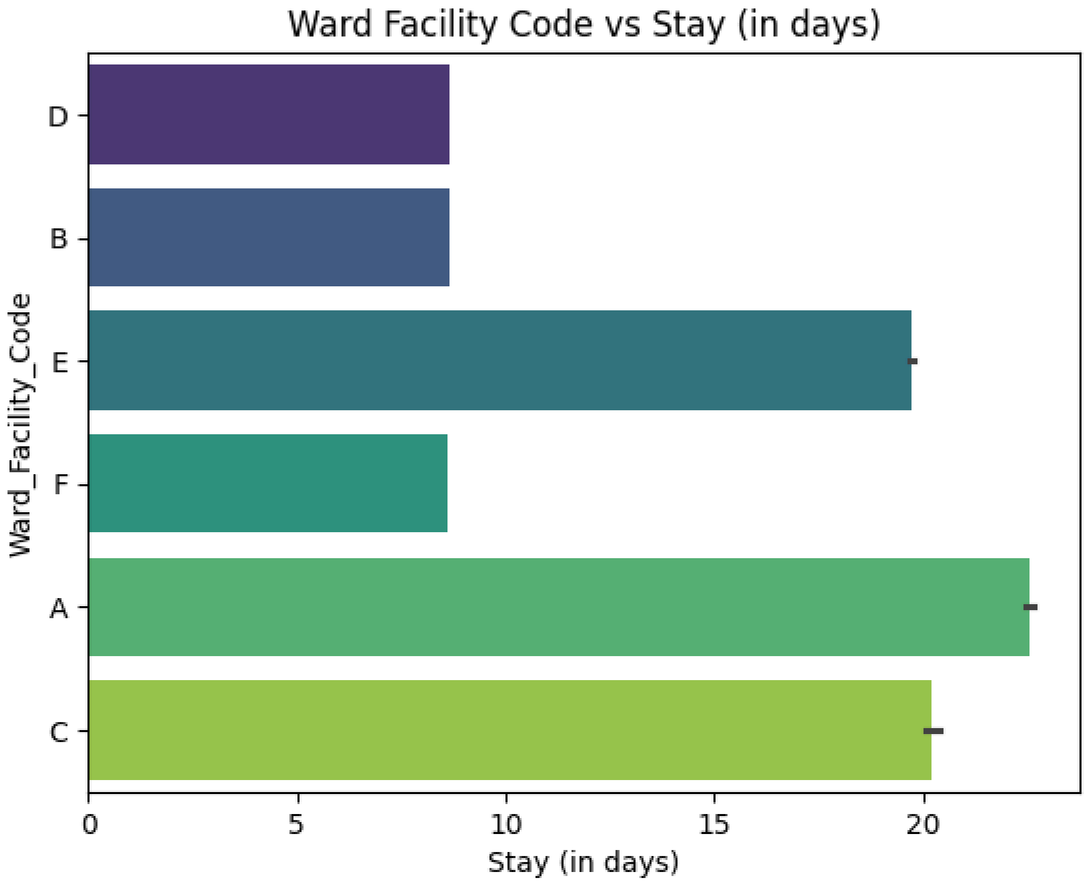


These is no high correlations among numeric features

In [ ]:
```
#@title Bivariate Analysis Categorical
print("Continuous Columns:",cat_col,"\n")
sns.barplot(x = "Stay (in days)", y = "Ward_Facility_Code", data = data1, palette='viridis')
plt.title("Ward Facility Code vs Stay (in days)")
plt.show()
```

```
Continuous Columns: Index(['Department', 'Ward_Facility_Code', 'doctor_name', 'Age', 'gender',
       'Type of Admission', 'Severity of Illness', 'health_conditions',
       'Insurance'],
      dtype='object')
```

```
/tmp/ipython-input-4006359160.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign th
e `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x = "Stay (in days)", y = "Ward_Facility_Code", data = data1, palette='viridis')
```



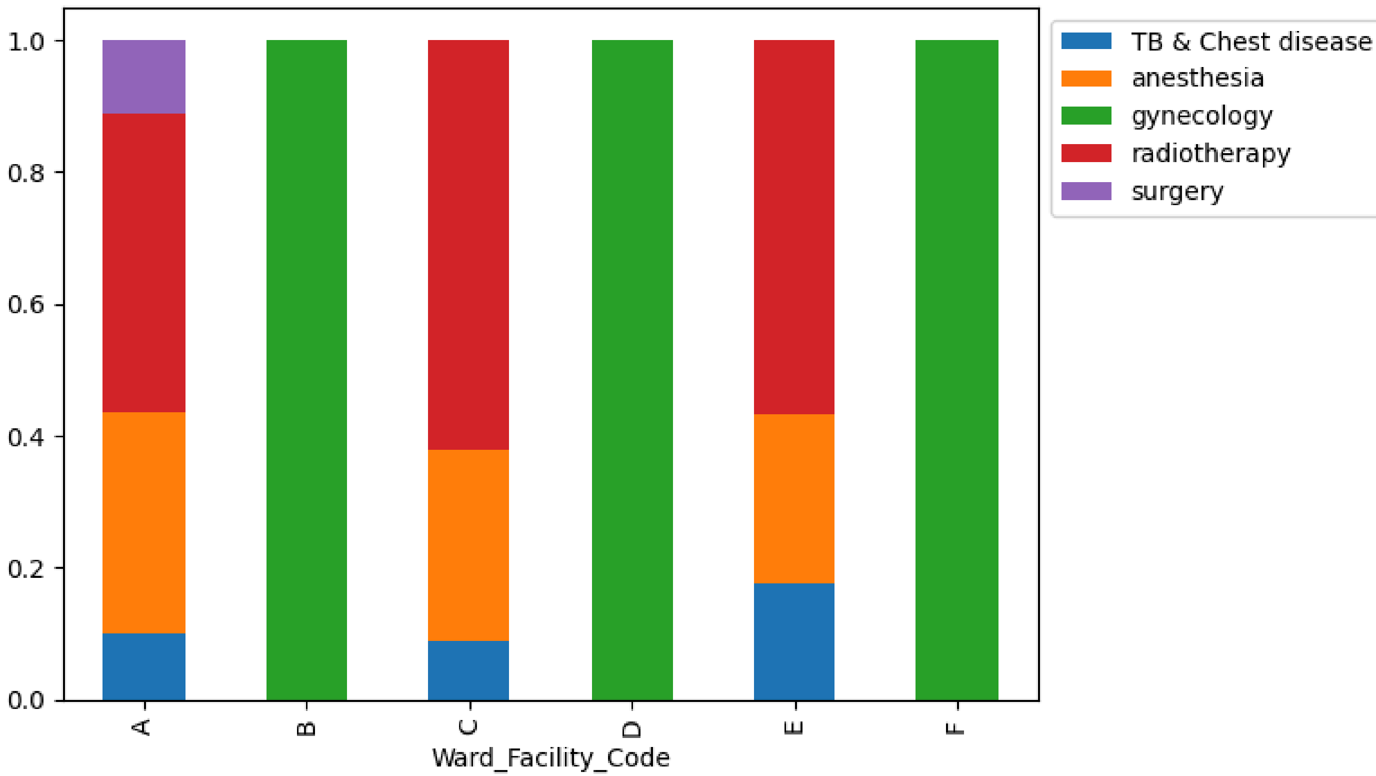
Differences exist in differences between D,B,F with E,A,C

In [ ]:
```
#  Look at the effect of two cataegorical variables on the dependent variable ot Interest
def stacked_barplot(data, predictor, target, norm):
  '''
  Makes a contingency table (frequency table): oredictor x target
    - Uses a dataframe
    - The feature trying to be used for prediction
    - The target that will show how many times the target is assigned per predictor
    - normalized values boolean option
  '''
  count = data[predictor].nunique() # Counts unique categories in predictor
  sorter = data[target].value_counts().index[-1] # picks the least frequent target level

  #tab1 = pd.crosstab(data[predictor], data[target], normalize='index') * 100 # optiom 1
  if norm == True:
    tab1 = pd.crosstab(data[predictor], data[target], normalize = 'index').sort_values(by=sorter
  else:
    tab1 = pd.crosstab(data[predictor], data[target]).sort_values(by=sorter, ascending=False) # 
  print(tab1)
  tab1.plot(kind = 'bar', stacked = True, figsize = (count + 1, 5)) # Stacked makes stacked bars
  plt.legend(loc = 'upper left', bbox_to_anchor = (1,1), frameon = True)
```

In [ ]:
```
#stacked_barplots = stacked_barplot(data1, 'Ward_Facility_Code', 'Stay (in days)', True)
```

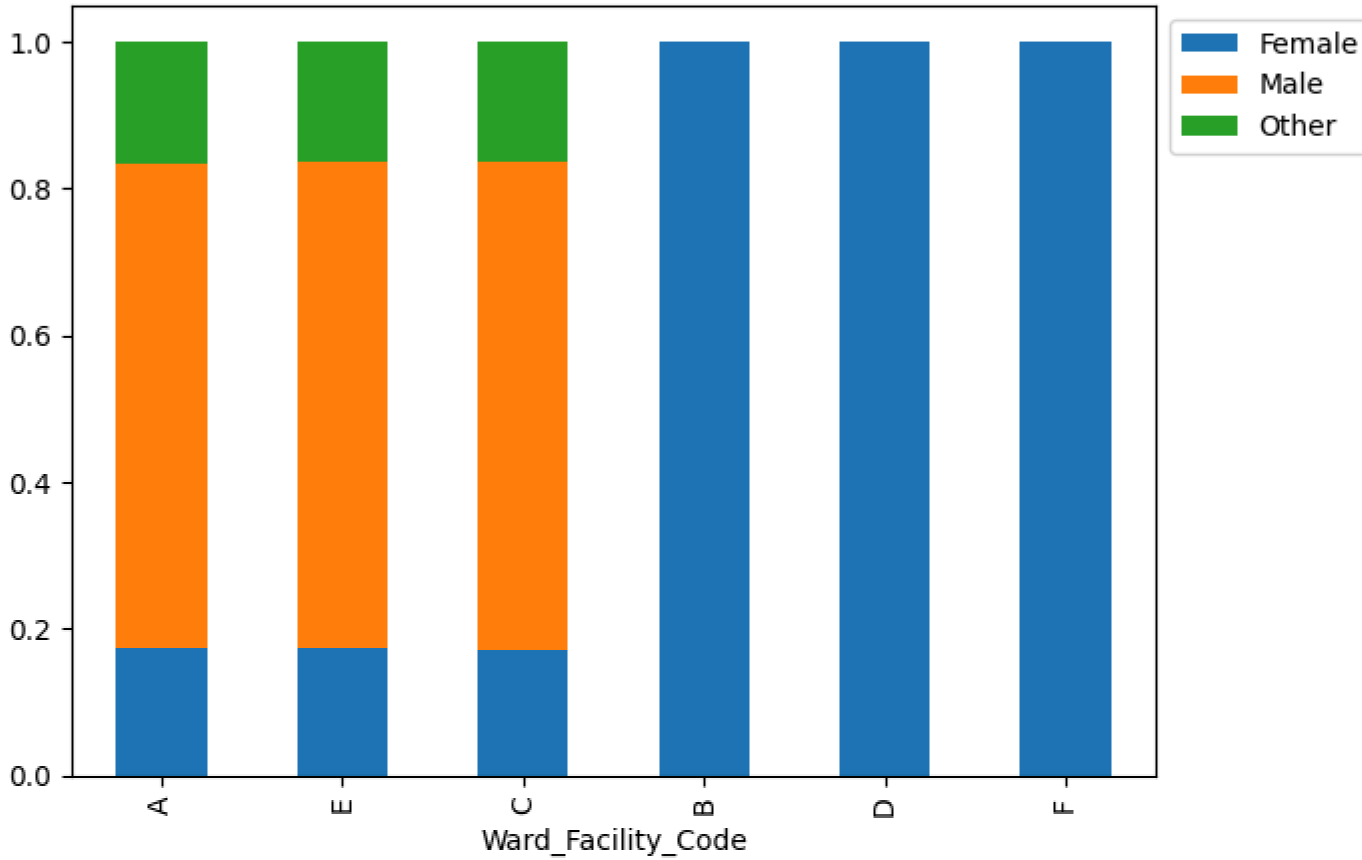
```
stacked_barplot(data1, 'Ward_Facility_Code', 'Department', True)
```

```
Department          TB & Chest disease  anesthesia  gynecology  radiotherapy  \
Ward_Facility_Code
A                             0.101158    0.335353         0.0      0.453116
B                             0.000000    0.000000         1.0      0.000000
C                             0.090361    0.287662         0.0      0.621977
D                             0.000000    0.000000         1.0      0.000000
E                             0.176799    0.255510         0.0      0.567691
F                             0.000000    0.000000         1.0      0.000000

Department           surgery
Ward_Facility_Code
A                   0.110374
B                   0.000000
C                   0.000000
D                   0.000000
E                   0.000000
F                   0.000000
```

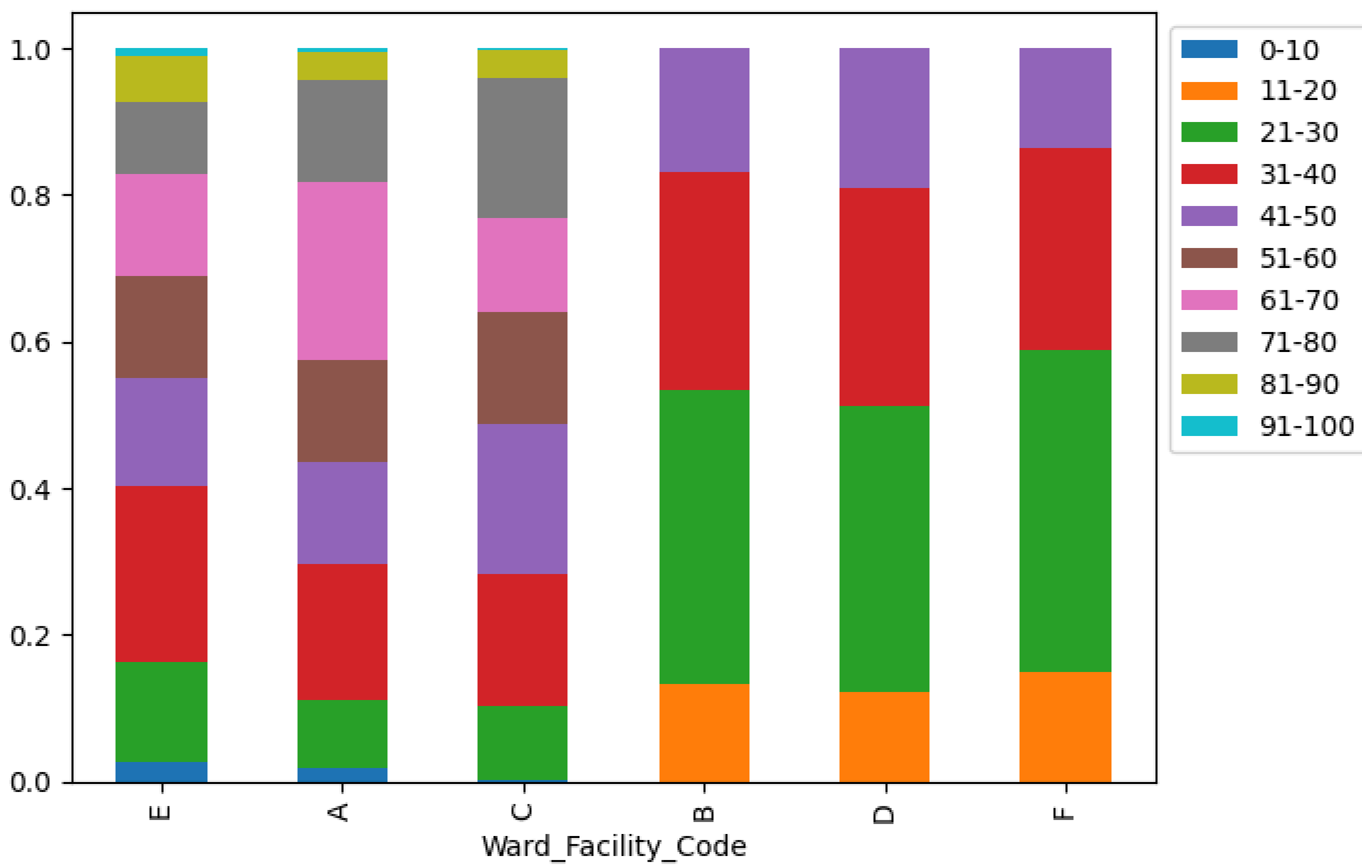


In [ ]:
```
stacked_barplot(data1, 'Ward_Facility_Code', 'gender', True)
stacked_barplot(data1, 'Ward_Facility_Code', 'Age', True)
stacked_barplot(data1, 'Ward_Facility_Code', 'Severity of Illness', True)
stacked_barplot(data1, 'Ward_Facility_Code', 'Type of Admission', True)
```

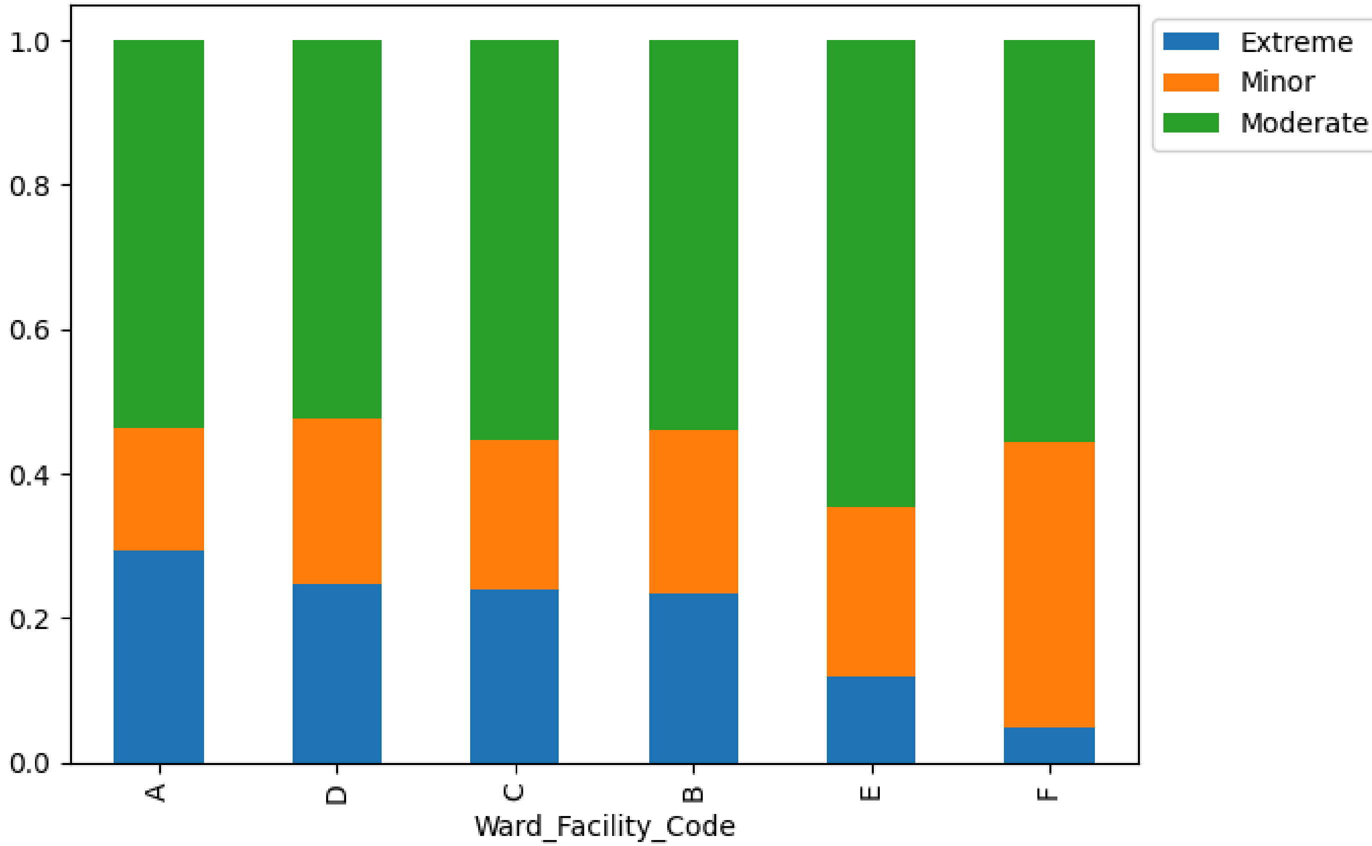
```
gender                  Female      Male     Other
Ward_Facility_Code
A                     0.175055  0.660158  0.164787
E                     0.174890  0.660977  0.164133
C                     0.171474  0.665137  0.163390
B                     1.000000  0.000000  0.000000
D                     1.000000  0.000000  0.000000
F                     1.000000  0.000000  0.000000
Age                       0-10     11-20     21-30     31-40     41-50  \
Ward_Facility_Code
E                     0.025646  0.000000  0.137931  0.238870  0.148636
A                     0.018818  0.000000  0.091598  0.186698  0.139653
C                     0.003151  0.000000  0.099267  0.181476  0.202987
B                     0.000000  0.134264  0.400606  0.296982  0.168147
D                     0.000000  0.123363  0.387922  0.297249  0.191466
F                     0.000000  0.148509  0.440724  0.273856  0.136911

Age                      51-60     61-70     71-80     81-90    91-100
Ward_Facility_Code
E                     0.137364  0.140112  0.099084  0.060897  0.011460
A                     0.137376  0.243153  0.138558  0.038689  0.005456
C                     0.152223  0.128383  0.192026  0.039186  0.001302
B                     0.000000  0.000000  0.000000  0.000000  0.000000
D                     0.000000  0.000000  0.000000  0.000000  0.000000
F                     0.000000  0.000000  0.000000  0.000000  0.000000
Severity of Illness   Extreme     Minor  Moderate
Ward_Facility_Code
A                     0.293485  0.169212  0.537303
D                     0.248196  0.228634  0.523170
C                     0.239981  0.206412  0.553607
B                     0.233162  0.226972  0.539866
E                     0.120452  0.233334  0.646214
F                     0.048466  0.394846  0.556688
Type of Admission   Emergency    Trauma    Urgent
Ward_Facility_Code
E                     0.242446  0.590853  0.166702
F                     0.291394  0.581717  0.126889
D                     0.363899  0.524573  0.111528
B                     0.178717  0.757366  0.063917
A                     0.145668  0.810724  0.043608
C                     0.607385  0.355758  0.036857
```

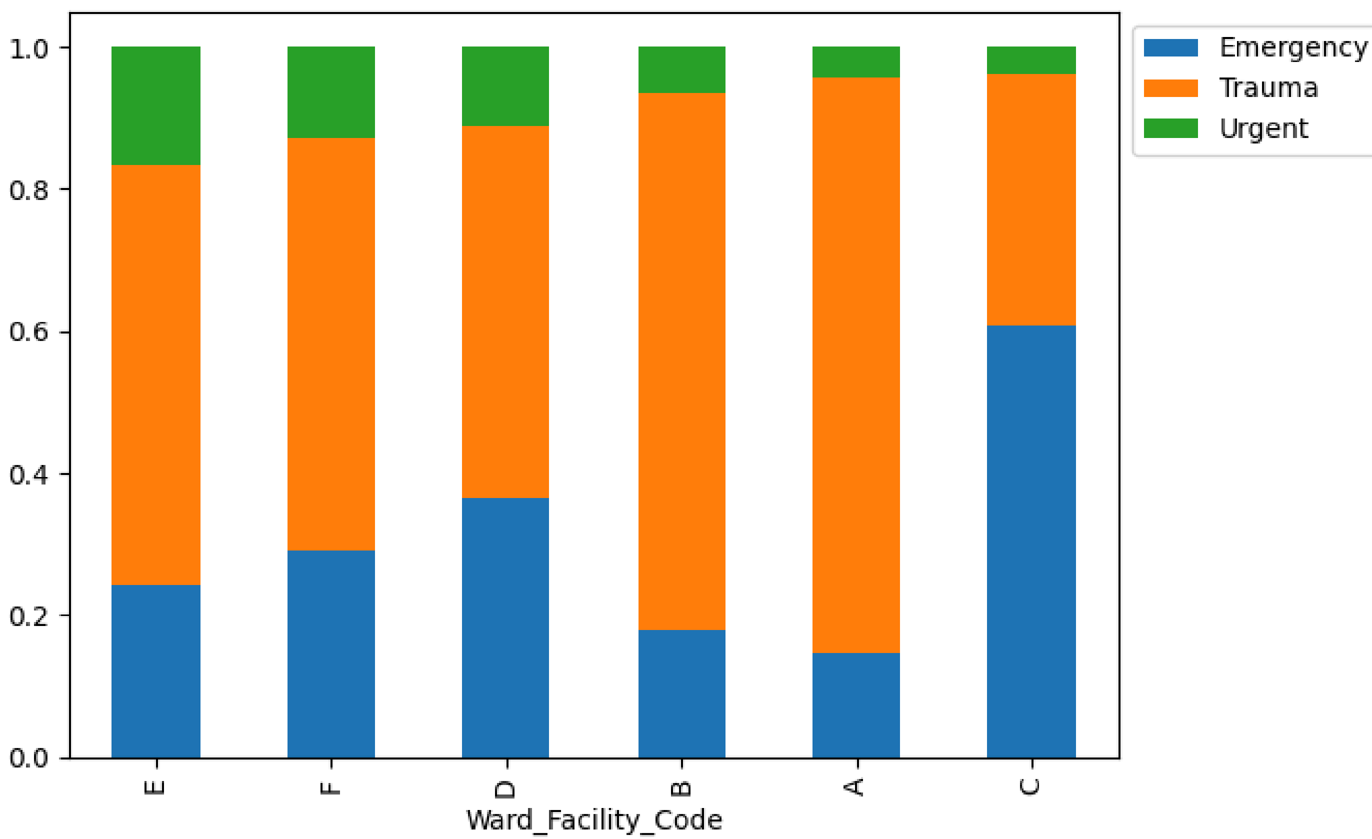


1.0
0.8
0.6
0.4
0.2
0.0
A
E
C
B
D
F
Ward_Facility_Code
Female
Male
Other



1.0
0.8
0.6
0.4
0.2
0.0
E
A
C
B
D
F
Ward_Facility_Code
0-10
11-20
21-30
31-40
41-50
51-60
61-70
71-80
81-90
91-100





Ward A is the only facility performing surgeries, and it shows a noticeably longer LOS compared to other wards, consistent with patients requiring extended recovery time.

Wards B, D, and F are dominated by gynecology cases with mostly female patients, which explains shorter and more consistent LOS patterns there.

LOS variation across wards (e.g., higher in A and C, lower in B/D/F) suggests that type of care delivered in each ward drives differences in patient stay length more than demographic balance alone.

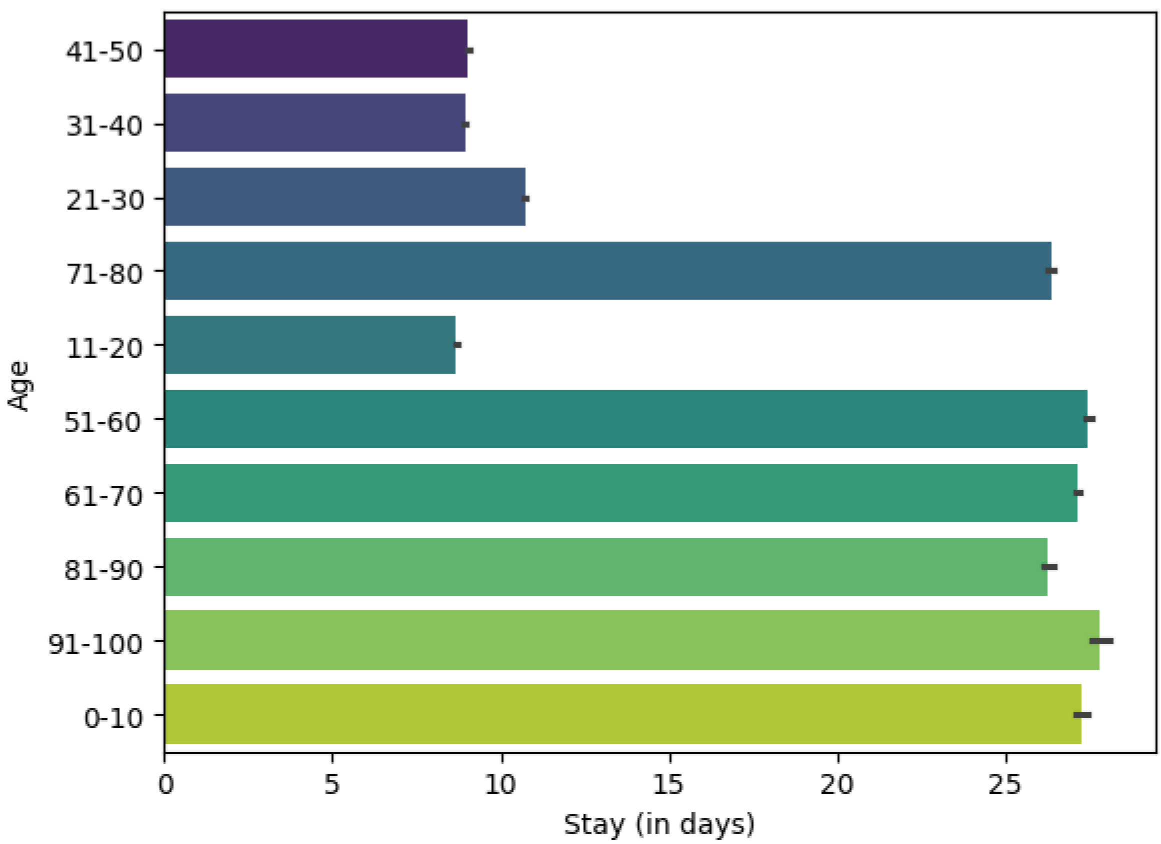
Although age groups are unevenly distributed across wards (younger patients clustered in B/D/F vs. wider age mix in A/C/E), the length of stay patterns align more strongly with ward specialization than with age.

This reinforces that clinical services (surgery, radiotherapy, gynecology, etc.) are the central determinant of LOS, while age is a secondary factor.

In [ ]:
```
sns.barplot(y = 'Age', x = 'Stay (in days)', data = data1, palette='viridis')
```

```
/tmp/ipython-input-3646498356.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign th
e `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(y = 'Age', x = 'Stay (in days)', data = data1, palette='viridis')
```

Out[ ]: `<Axes: xlabel='Stay (in days)', ylabel='Age'>`



In [ ]:
```
data1.groupby('doctor_name')['Department'].agg(
    Department_name ='unique', # returns the unique departments that doctor worked in.
    Patients_Treated = 'count' # counts how many rows (patients) that doctor had.
).sort_values(by='Patients_Treated', ascending=False)
```

Out[ ]:

doctor_name	Department_name	Patients_Treated
Dr Sarah	[gynecology]	99596
Dr Olivia	[gynecology]	98352
Dr Sophia	[gynecology]	74753
Dr Nathan	[gynecology]	70777
Dr Sam	[radiotherapy]	55711
Dr John	[TB & Chest disease, anesthesia, radiotherapy]	51263
Dr Mark	[anesthesia, TB & Chest disease]	44410
Dr Isaac	[surgery]	3359
Dr Simon	[surgery]	1779

In [ ]:

```
data1.select_dtypes(include = ['object', 'category']).columns.tolist()
```

Out[ ]:

```
['Department',
 'Ward_Facility_Code',
 'doctor_name',
 'Age',
 'gender',
 'Type of Admission',
 'Severity of Illness',
 'health_conditions',
 'Insurance']
```

In [ ]:

```
# @ title ML Modeling
data2 = pd.get_dummies(
    data1,
    columns = data1.select_dtypes(include = ['object', 'category']).columns.tolist(),
    drop_first = True # get n-1 columns for each feature
    )
```

In [ ]:

```
x = data2.drop('Stay (in days)', axis=1) # drop column
y = data2['Stay (in days)']
```

In [ ]:

```
print(x.shape)
print(y.shape)

# Data split
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

# Train Decision Tree
model = DecisionTreeRegressor(random_state=42)
```

```
model.fit(x_train, y_train)

# Predict on test data
y_pred = model.predict(x_test)

# Report
print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R2 Score:", r2_score(y_test, y_pred))

# Confusion metrics
cf = confusion_matrix(y_test, y_pred)
print(cf)
print(classification_report(y_test, y_pred))

# Visualize in heatmap
sns.heatmap(cf, annot=True, cmap='crest', vmax=1, vmin = -1)
```

In [ ]:

```
print(x.shape)
print(y.shape)

# Data split
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score as r2


x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, shuffle = True, random_

def adj_r2_score(predictors, targets, predictions):
    r2 = r2_score(targets, predictions)
    n = predictors.shape[0]
    k = predictors.shape[1]
    adjusted_r2 = 1 - ((1 - r2) * (n - 1) / (n - k - 1))
    return adjusted_r2

# Mean absoluate percentage error
def mape_score(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

def model_performance_regression(model, predictors, target):
  pred = model.predict(predictors)
  r2 = r2_score(target,pred)
  adjr2 = adj_r2_score(predictors, target, pred)
  rmse = np.sqrt(mean_squared_error(target, pred))
  mae = mean_absolute_error(target, pred)
  mape = mape_score(target, pred)

  df_performance = pd.DataFrame({
      'Model': type(model).__name__,
      'R2_Score': r2,
      'Adj_R2_Score': adjr2,
      'RMSE': rmse,
      'MAPE': mape,
      'MAE': mae
```

```python
    }, index=[0])
    return df_performance
```

```
(500000, 43)
(500000,)
```

In [ ]:

```python
dt_regressor = DecisionTreeRegressor(random_state=42)
dt_regressor.fit(x_train, y_train)

#model_performance_regression(dt_regresspr, x_train, y_train)
```

Out[ ]:

```
DecisionTreeRegressor

DecisionTreeRegressor(random_state=42)
```

In [ ]:

```python
dt_regressor_perf_test = model_performance_regression(dt_regressor, x_test, y_test)
dt_regressor_perf_test
```

Out[ ]:

	Model	R2_Score	Adj_R2_Score	RMSE	MAPE	MAE
0	DecisionTreeRegressor	0.943853	0.943836	1.877161	9.797425	1.183893

In [ ]:

```python
# Visualize Trees to see most important factors in making decision
from sklearn import tree
```

In [ ]:

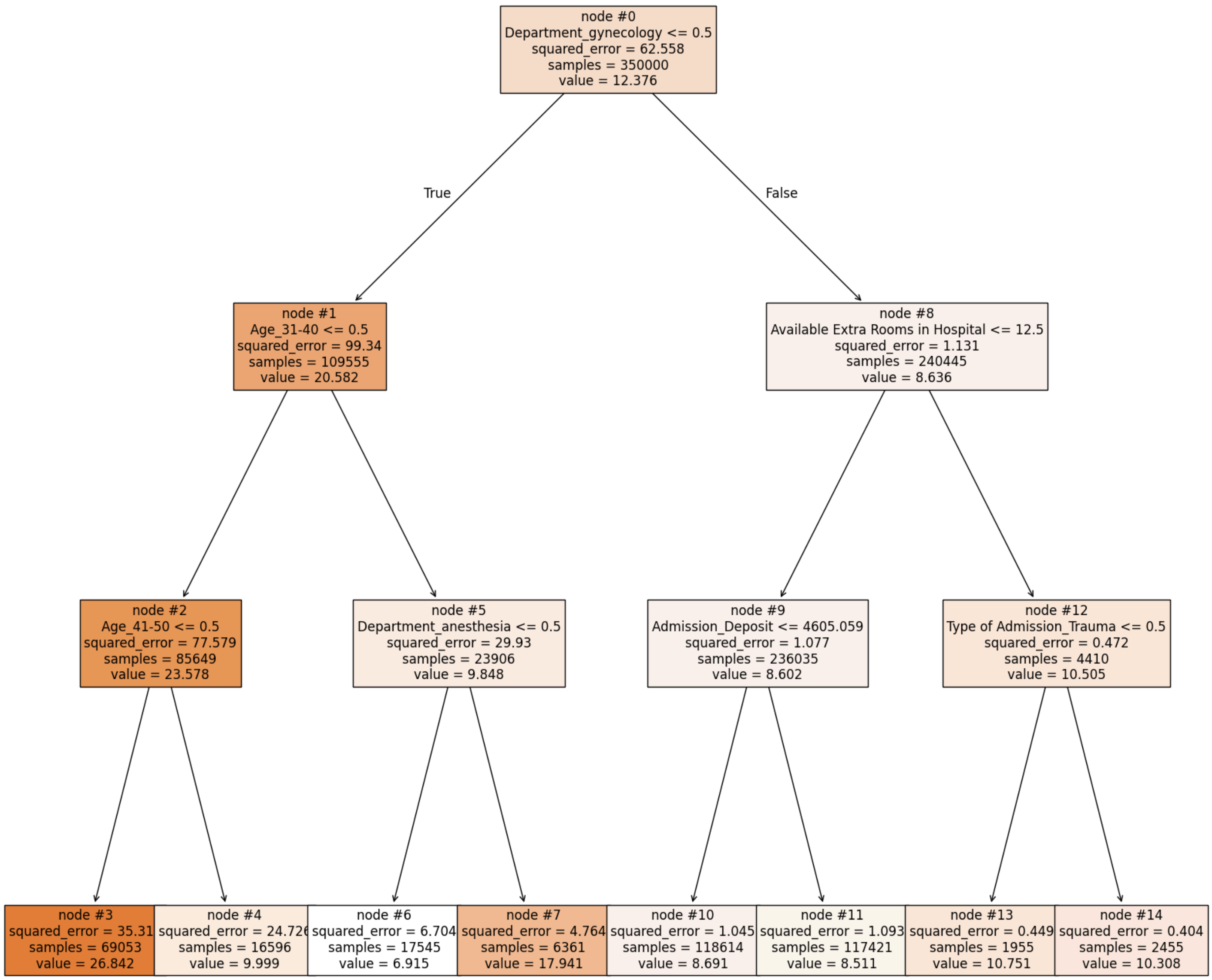
```python
features = list(x.columns)
features
```

```
Out[ ]: ['Available Extra Rooms in Hospital',
 'staff_available',
 'patientid',
 'Visitors with Patient',
 'Admission_Deposit',
 'Department_anesthesia',
 'Department_gynecology',
 'Department_radiotherapy',
 'Department_surgery',
 'Ward_Facility_Code_B',
 'Ward_Facility_Code_C',
 'Ward_Facility_Code_D',
 'Ward_Facility_Code_E',
 'Ward_Facility_Code_F',
 'doctor_name_Dr John',
 'doctor_name_Dr Mark',
 'doctor_name_Dr Nathan',
 'doctor_name_Dr Olivia',
 'doctor_name_Dr Sam',
 'doctor_name_Dr Sarah',
 'doctor_name_Dr Simon',
 'doctor_name_Dr Sophia',
 'Age_11-20',
 'Age_21-30',
 'Age_31-40',
 'Age_41-50',
 'Age_51-60',
 'Age_61-70',
 'Age_71-80',
 'Age_81-90',
 'Age_91-100',
 'gender_Male',
 'gender_Other',
 'Type of Admission_Trauma',
 'Type of Admission_Urgent',
 'Severity of Illness_Minor',
 'Severity of Illness_Moderate',
 'health_conditions_Diabetes',
 'health_conditions_Heart disease',
 'health_conditions_High Blood Pressure',
 'health_conditions_Other',
 'health_conditions_Unknown',
 'Insurance_Yes']
```

```
In [ ]: # Visualize a shallow decision tree
dt_regressor_visualize = DecisionTreeRegressor(max_depth=3, random_state=42)
dt_regressor_visualize.fit(x_train, y_train)
```

```
Out[ ]: DecisionTreeRegressor

DecisionTreeRegressor(max_depth=3, random_state=42)
```

```
In [ ]: plt.figure(figsize = (20,20))
tree.plot_tree(dt_regressor_visualize, feature_names=features, filled = True, fontsize= 12, node_
```



In [ ]:
```
print(tree.export_text(dt_regressor_visualize, feature_names=features, show_weights=True)) # Migh
```

```
|--- Department_gynecology <= 0.50
|   |--- Age_31-40 <= 0.50
|   |   |--- Age_41-50 <= 0.50
|   |   |   |--- value: [26.84]
|   |   |--- Age_41-50 >  0.50
|   |   |   |--- value: [10.00]
|   |--- Age_31-40 >  0.50
|   |   |--- Department_anesthesia <= 0.50
|   |   |   |--- value: [6.91]
|   |   |--- Department_anesthesia >  0.50
|   |   |   |--- value: [17.94]
|--- Department_gynecology >  0.50
|   |--- Available Extra Rooms in Hospital <= 12.50
|   |   |--- Admission_Deposit <= 4605.06
|   |   |   |--- value: [8.69]
|   |   |--- Admission_Deposit >  4605.06
|   |   |   |--- value: [8.51]
|   |--- Available Extra Rooms in Hospital >  12.50
|   |   |--- Type of Admission_Trauma <= 0.50
|   |   |   |--- value: [10.75]
|   |   |--- Type of Admission_Trauma >  0.50
|   |   |   |--- value: [10.31]
```

In [ ]:

```python
# Bagging (Bootstrap Aggragating)
from sklearn.ensemble import BaggingRegressor
# Decision trees: "Let's make predictions by recursively splitting the data into groups that are
# Bagging: “Let’s average many full-grown trees trained on bootstraps to reduce variance.”
# Random Forest: “Let’s average many bootstrapped trees, but also force them to look at differen

bagging_estimator = BaggingRegressor(random_state= 42)
bagging_estimator.fit(x_train, y_train)
```

Out[ ]:

```
BaggingRegressor

BaggingRegressor(random_state=42)
```

In [ ]:

```python
bagging_estimator_perf_test = model_performance_regression(bagging_estimator, x_test, y_test)
bagging_estimator_perf_test
```

Out[ ]:

	Model	R2_Score	Adj_R2_Score	RMSE	MAPE	MAE
0	BaggingRegressor	0.969072	0.969063	1.393198	7.877372	0.931766

In [ ]:

```python
from sklearn.ensemble import RandomForestRegressor

randoma_forest_estimator = RandomForestRegressor(random_state=42)
randoma_forest_estimator.fit(x_train, y_train)
```

Out[ ]:

```
RandomForestRegressor

RandomForestRegressor(random_state=42)
```

In [ ]:

```python
randoma_forest_estimator_perf_test = model_performance_regression(randoma_forest_estimator, x_te
randoma_forest_estimator_perf_test
```

Out[ ]:

	Model	R2_Score	Adj_R2_Score	RMSE	MAPE	MAE
0	RandomForestRegressor	0.971928	0.97192	1.327311	7.527352	0.888548

In [ ]:
```
from sklearn.ensemble import AdaBoostRegressor

adaboost_estimator = AdaBoostRegressor(random_state=42)
adaboost_estimator.fit(x_train, y_train)
```

Out[ ]:

```
AdaBoostRegressor

AdaBoostRegressor(random_state=42)
```

In [ ]:
```
adaboost_estimator_perf_test = model_performance_regression(adaboost_estimator, x_test, y_test)
adaboost_estimator_perf_test
```

Out[ ]:

	Model	R2_Score	Adj_R2_Score	RMSE	MAPE	MAE
0	AdaBoostRegressor	0.917701	0.917677	2.27266	13.252706	1.533617

In [ ]:
```
from sklearn.ensemble import GradientBoostingRegressor

gradient_boosting_estimator = GradientBoostingRegressor(random_state=42)
gradient_boosting_estimator.fit(x_train, y_train)
```

Out[ ]:

```
GradientBoostingRegressor

GradientBoostingRegressor(random_state=42)
```

In [ ]:
```
gradient_boosting_estimator_perf_test = model_performance_regression(gradient_boosting_estimator
gradient_boosting_estimator_perf_test
```

Out[ ]:

	Model	R2_Score	Adj_R2_Score	RMSE	MAPE	MAE
0	GradientBoostingRegressor	0.949619	0.949604	1.778165	10.175947	1.204983

In [ ]:
```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.12/dist-packages (3.0.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-packages (from xgboost)
(2.0.2)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.12/dist-packages (from
xgboost) (2.27.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.12/dist-packages (from xgboost)
(1.16.1)
```

In [ ]:
```
from xgboost import XGBRegressor

xgboost_estimator = XGBRegressor(random_state=42)
xgboost_estimator.fit(x_train, y_train)
```

Out[ ]:

XGBRegressor

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             feature_weights=None, gamma=None, grow_policy=None,
             importance_type=None, interaction_constraints=None,
             learning_rate=None, max_bin=None, max_cat_threshold=None,
             max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
             max_leaves=None, min_child_weight=None, missing=nan,
```

In [ ]:

```
xgboost_estimator_perf_test = model_performance_regression(xgboost_estimator, x_test, y_test)
xgboost_estimator_perf_test
```

Out[ ]:

	Model	R2_Score	Adj_R2_Score	RMSE	MAPE	MAE
0	XGBRegressor	0.964042	0.964031	1.502228	8.85494	1.031396

In [ ]:

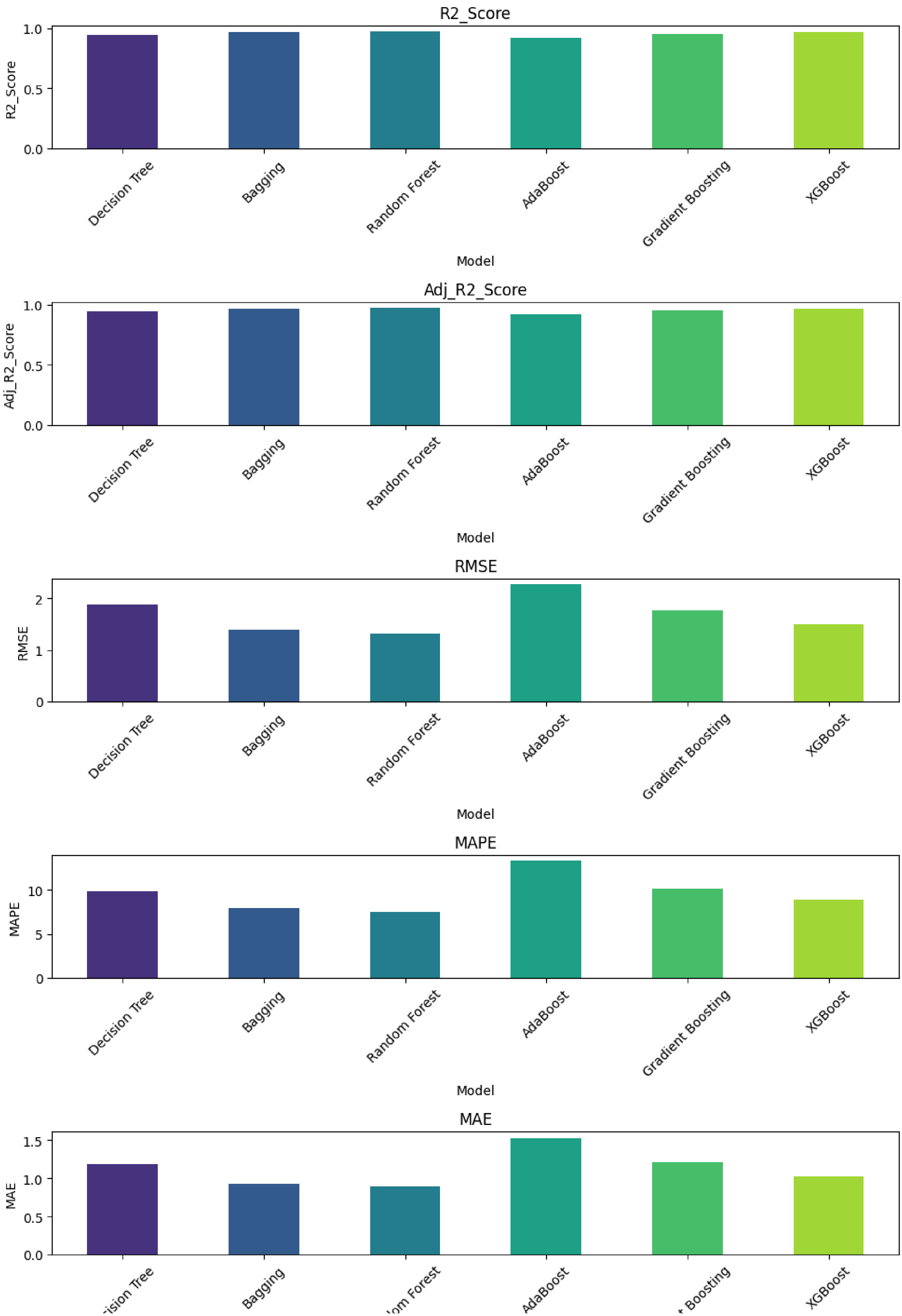
```
models_test_comp_df = pd.concat(
    [
        dt_regressor_perf_test.T,
        bagging_estimator_perf_test.T,
        randoma_forest_estimator_perf_test.T,
        adaboost_estimator_perf_test.T,
        gradient_boosting_estimator_perf_test.T,
        xgboost_estimator_perf_test.T
    ],
    axis=1
)

models_test_comp_df.columns = [
    'Decision Tree',
    'Bagging',
    'Random Forest',
    'AdaBoost',
    'Gradient Boosting',
    'XGBoost'
]

models_test_comp_df
```

Out[ ]:

	Decision Tree	Bagging	Random Forest	AdaBoost	Gı
Model	DecisionTreeRegressor	BaggingRegressor	RandomForestRegressor	AdaBoostRegressor	GradientB
R2_Score	0.943853	0.969072	0.971928	0.917701	
Adj_R2_Score	0.943836	0.969063	0.97192	0.917677	
RMSE	1.877161	1.393198	1.327311	2.27266	
MAPE	9.797425	7.877372	7.527352	13.252706	
MAE	1.183893	0.931766	0.888548	1.533617	

In [ ]:

```
# Transpose the DataFrame to have models as rows and metrics as columns for easier plotting
models_plot_df = models_test_comp_df.T.drop('Model', axis=1)

# Create subplots for each metric
fig, axes = plt.subplots(nrows=len(models_plot_df.columns), figsize=(10, 15))

# Define a color palette
colors = sns.color_palette('viridis', len(models_plot_df))

for i, col in enumerate(models_plot_df.columns):
    models_plot_df[col].plot(kind='bar', ax=axes[i], color=colors)
    axes[i].set_title(col)
    axes[i].set_ylabel(col)
    axes[i].set_xlabel("Model")
    axes[i].tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```



R2_Score
R2_Score
1.0
0.5
0.0
Decision Tree
Bagging
Random Forest
AdaBoost
Gradient Boosting
XGBoost
Model
Adj_R2_Score
Adj_R2_Score
1.0
0.5
0.0
Decision Tree
Bagging
Random Forest
AdaBoost
Gradient Boosting
XGBoost
Model
RMSE
RMSE
2
1
0
Decision Tree
Bagging
Random Forest
AdaBoost
Gradient Boosting
XGBoost
Model
MAPE
MAPE
10
5
0
Decision Tree
Bagging
Random Forest
AdaBoost
Gradient Boosting
XGBoost
Model
MAE
MAE
1.5
1.0
0.5
0.0
Bagging
AdaBoost
XGBoost

In [ ]:

```
rf_tuned = RandomForestRegressor(random_state=42)

rf_parameters = {
    'n_estimators': [100, 110, 120, 200],
    'max_depth': [None, 10, 15, 20,],
    'max_features': [0.8, 1.0]
}
```

In [ ]:

```
from seaborn.axisgrid import Grid
rf_grid_obj = GridSearchCV(rf_tuned, rf_parameters, cv=5, scoring = 'neg_mean_squared_error')
rf_grid_obj.fit(x_train, y_train)
```

In [ ]:

```
rf_tuned_regressor = rf_grid_obj.best_estimator_
rf_tuned_regressor.fit(x_train, y_train)
```

In [ ]:

```
rf_tuned_regressor_perf_test = model_performance_regression(rf_tuned_regressor, x_test, y_test)
rf_tuned_regressor_perf_test
```

In [ ]:

```
pd.concat([
    models_test_comp_df,
    rf_tuned_regressor_perf_test.T
], axis=1).T
```

In [ ]:

```
importances = rf_tuned_regressor.feature_importances_
indices = np.argsort(importances)
plt.figure(figsize=(10, 10))
plt.title('Feature Importances')
plt.barh(range(len(features)), importances[indices], color='violet', align='center');
plt.yticks(range(len(features)), [features[i] for i in indices]);
plt.xlabel('Relative Importance')
```