In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Basic Analysis and understanding of the data

In [2]:
```python
#Load the dataset
df = pd.read_csv(r"D:\DSML class\Data\Hospital_Data_resource_allocation.csv")
```

Observation of the data

In [3]:
```python
# Display first five rows of the dataset
print('\nFirst five rows of the dataset')
df.head(5)
```

```
First five rows of the dataset
```

Out[3]:

	case_id	Hospital_code	Hospital_type_code	City_Code_Hospital	Hospital_region_code	Available Extra Rooms in Hospital	Department	Ward_Type	Ward_Facility
0	1	8	c	3	Z	3	radiotherapy	R	
1	2	2	c	5	Z	2	radiotherapy	S	
2	3	10	e	1	X	2	anesthesia	S	
3	4	26	b	2	Y	2	radiotherapy	R	
4	5	26	b	2	Y	2	radiotherapy	S	

In [4]:
```python
df.shape
```

Out[4]:
```
(318438, 18)
```

In [5]:

```
# Getting the overview of the dataset structure
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 318438 entries, 0 to 318437
Data columns (total 18 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   case_id                            318438 non-null  int64  
 1   Hospital_code                      318438 non-null  int64  
 2   Hospital_type_code                 318438 non-null  object 
 3   City_Code_Hospital                 318438 non-null  int64  
 4   Hospital_region_code               318438 non-null  object 
 5   Available Extra Rooms in Hospital  318438 non-null  int64  
 6   Department                         318438 non-null  object 
 7   Ward_Type                          318438 non-null  object 
 8   Ward_Facility_Code                 318438 non-null  object 
 9   Bed Grade                          318325 non-null  float64
 10  patientid                          318438 non-null  int64  
 11  City_Code_Patient                  313906 non-null  float64
 12  Type of Admission                  318438 non-null  object 
 13  Severity of Illness                318438 non-null  object 
 14  Visitors with Patient              318438 non-null  int64  
 15  Age                                318438 non-null  object 
 16  Admission_Deposit                  318438 non-null  int64  
 17  Stay                               318438 non-null  object 
dtypes: float64(2), int64(7), object(9)
memory usage: 43.7+ MB
```

In [6]:

```
#Defining Numerical and Categorical columns
numerical_columns = df.select_dtypes(include='number')
categorical_columns = df.select_dtypes(include='object')
```

In [7]:

```
# Checking the summary Statistics of the numerical columns
df.describe()
```

Out[7]:

	case_id	Hospital_code	City_Code_Hospital	Available Extra Rooms in Hospital	Bed Grade	patientid	City_Code_Patient	Visitors with Patient	Ac
ount	318438.000000	318438.000000	318438.000000	318438.000000	318325.000000	318438.000000	313906.000000	318438.000000	
ean	159219.500000	18.318841	4.771717	3.197627	2.625807	65747.579472	7.251859	3.284099	
std	91925.276847	8.633755	3.102535	1.168171	0.873146	37979.936440	4.745266	1.764061	
min	1.000000	1.000000	1.000000	0.000000	1.000000	1.000000	1.000000	0.000000	
25%	79610.250000	11.000000	2.000000	2.000000	2.000000	32847.000000	4.000000	2.000000	
50%	159219.500000	19.000000	5.000000	3.000000	3.000000	65724.500000	8.000000	3.000000	
75%	238828.750000	26.000000	7.000000	4.000000	3.000000	98470.000000	8.000000	4.000000	
max	318438.000000	32.000000	13.000000	24.000000	4.000000	131624.000000	38.000000	32.000000	

In [8]:

```
#Unique values and it's count unique of all columns
print('\nUnique values in categorical columns')
categorical_columns.nunique()
```

```
Unique values in categorical columns
```

Out[8]:

```
Hospital_type_code       7
Hospital_region_code     3
Department               5
Ward_Type                6
Ward_Facility_Code       6
Type of Admission        3
Severity of Illness      3
Age                     10
Stay                    11
dtype: int64
```

Data Processing

In [9]:
```
# Duplicate value check
df[df.duplicated()]
```

Out[9]:

tal_type_code	City_Code_Hospital	Hospital_region_code	Available Extra Rooms in Hospital	Department	Ward_Type	Ward_Facility_Code	Bed Grade	patientid	City_Cod

In [10]:
```
# Checking missing values
df.isna().sum()
```

Out[10]:
```
case_id                                0
Hospital_code                          0
Hospital_type_code                     0
City_Code_Hospital                     0
Hospital_region_code                   0
Available Extra Rooms in Hospital      0
Department                             0
Ward_Type                              0
Ward_Facility_Code                     0
Bed Grade                            113
patientid                              0
City_Code_Patient                   4532
Type of Admission                      0
Severity of Illness                    0
Visitors with Patient                  0
Age                                    0
Admission_Deposit                      0
Stay                                   0
dtype: int64
```

In [11]:
```
df.groupby(['patientid', 'City_Code_Patient']).count().reset_index()['City_Code_Patient'].isna().sum()
```

Out[11]:
```
0
```

Insight:

- There are missing values in Bed grade and City code of the patient.
- The analysis shows that the all the patient's city code has been collected at some point of time during their visits to the hospitals.

Abnormality check

In [12]:
```
#Check for abnormal values in Age group
df['Age'].unique()
```

Out[12]:
```
array(['51-60', '71-80', '31-40', '41-50', '81-90', '61-70', '21-30',
       'Nov-20', '0-10', '91-100'], dtype=object)
```

11-20 age group has been recorded as Nov-20 needs to be changed to 11-20

In [301]:
```
# Create a function to correct age group name
def groupNameChange(x):
    if x == 'Nov-20':
        return '11-20'
    else:
        return x
```

In [14]:
```
df['Age'] = df['Age'].apply(groupNameChange)
```

In [303]:
```python
#Checking for abnormalities in Age
df['Age'].unique()
```

Out[303]:
```
array(['51-60', '71-80', '31-40', '41-50', '81-90', '61-70', '21-30',
       '11-20', '0-10', '91-100'], dtype=object)
```

In [302]:
```python
#Checking for abnormalities in Stay
df['Stay'].unique()
```

Out[302]:
```
array(['0-10', '41-50', '31-40', '11-20', '51-60', '21-30', '71-80',
       'More than 100 Days', '81-90', '61-70', '91-100'], dtype=object)
```

Again 11-20 age group has been recorded as Nov-20 needs to be changed to 11-20

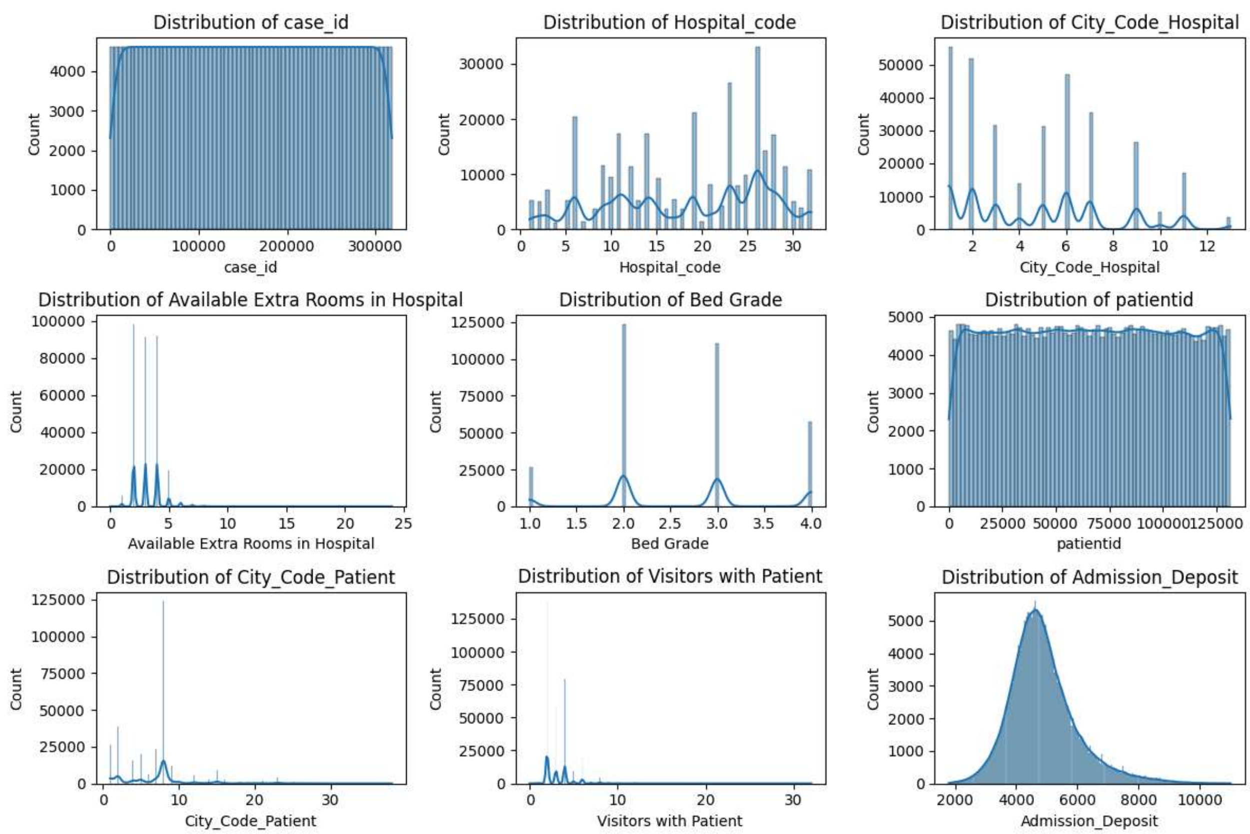
In [17]:
```python
df['Stay'] = df['Stay'].apply(groupNameChange)
```

In [18]:
```python
df['Stay'].unique()
```

Out[18]:
```
array(['0-10', '41-50', '31-40', '11-20', '51-60', '21-30', '71-80',
       'More than 100 Days', '81-90', '61-70', '91-100'], dtype=object)
```

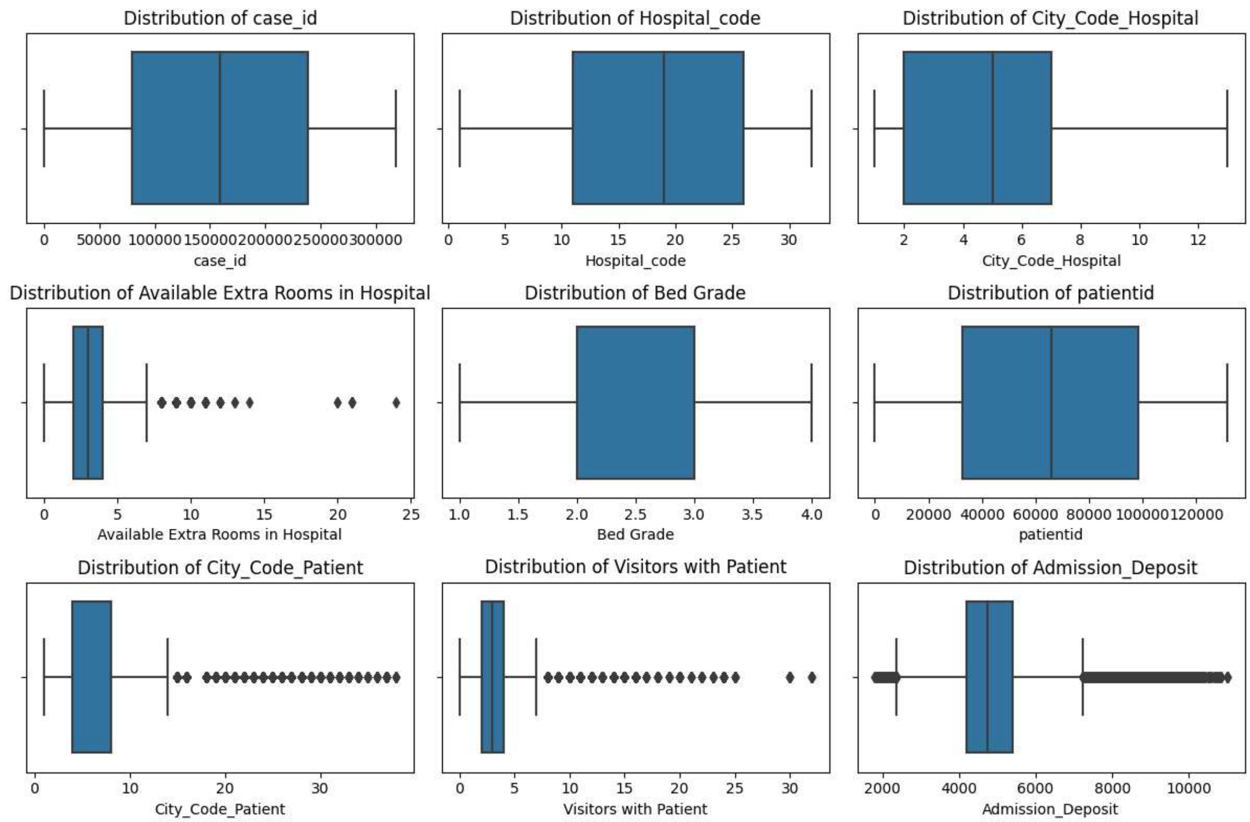
Univariate analysis

In [19]:
```python
plt.figure(figsize=(12,8))
for i, column in enumerate(numerical_columns.columns, 1):
    plt.subplot(3,3,i)
    sns.histplot(df[column], kde=True)
    plt.title(f'Distribution of {column}')
plt.tight_layout()
plt.show()
```



In [305]:

```python
# Plotting box plot for all numerical columns
plt.figure(figsize=(12,8))
for i, column in enumerate(numerical_columns.columns, 1):
    plt.subplot(3,3,i)
    sns.boxplot(data=df, x=column)
    plt.title(f'Distribution of {column}')
plt.tight_layout()
plt.show()
```

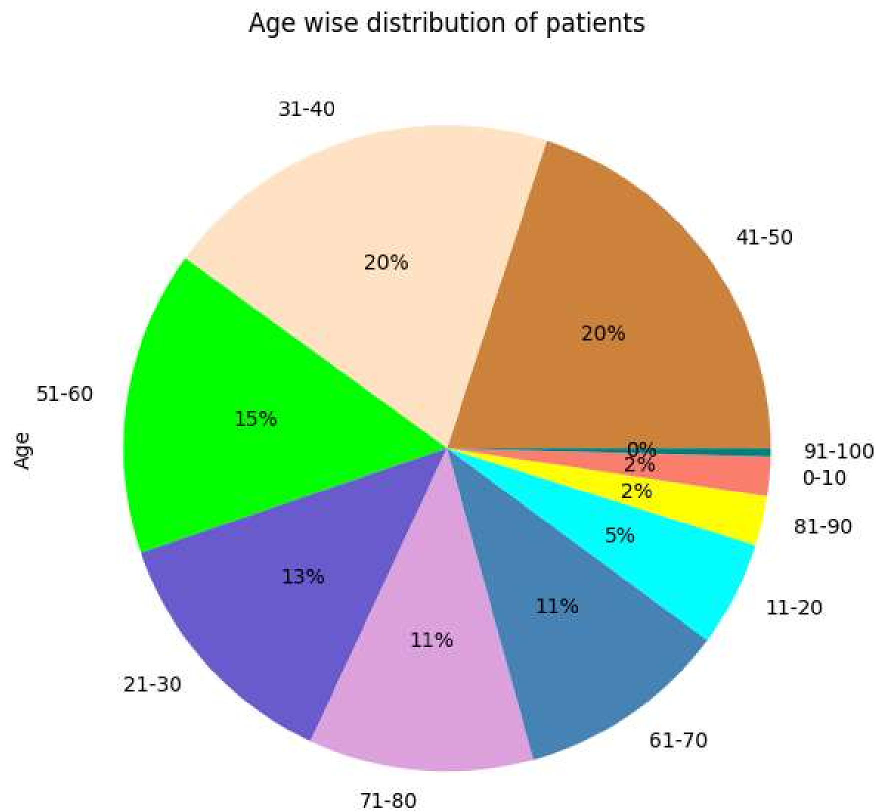


Exploring Patient Demographics

Patient age wise analysis

In [195]:

```
#Age wise analysis
plt.figure(figsize=(10,6))
df['Age'].value_counts().plot(kind='pie', autopct='%1.0f%%', colors=['peru', 'bisque', 'lime', 'slateblue', 'pl
plt.title('Age wise distribution of patients')
plt.tight_layout()
plt.show()
```



In [306]:

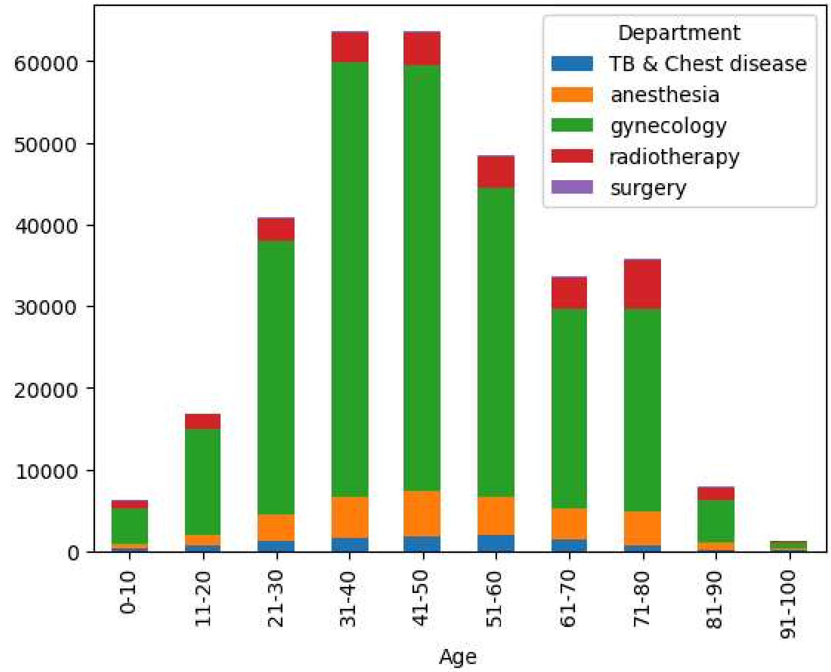
```
# Age vs department
ad = pd.crosstab(df['Age'], df['Department'], margins=True)
ad
```

Out[306]:

Department Age	TB & Chest disease	anesthesia	gynecology	radiotherapy	surgery	All
0-10	387	464	4362	943	98	6254
11-20	694	1315	13021	1694	44	16768
21-30	1237	3320	33437	2771	78	40843
31-40	1563	5030	53296	3626	124	63639
41-50	1717	5608	52212	4031	181	63749
51-60	1858	4875	37798	3779	204	48514
61-70	1308	3860	24460	3864	195	33687
71-80	704	4062	24925	5903	198	35792
81-90	76	913	5236	1598	67	7890
91-100	42	202	739	307	12	1302
All	9586	29649	249486	28516	1201	318438

In [160]:
```
ad.plot(kind='bar', stacked=True)
```

Out[160]: <Axes: xlabel='Age'>



Insights:

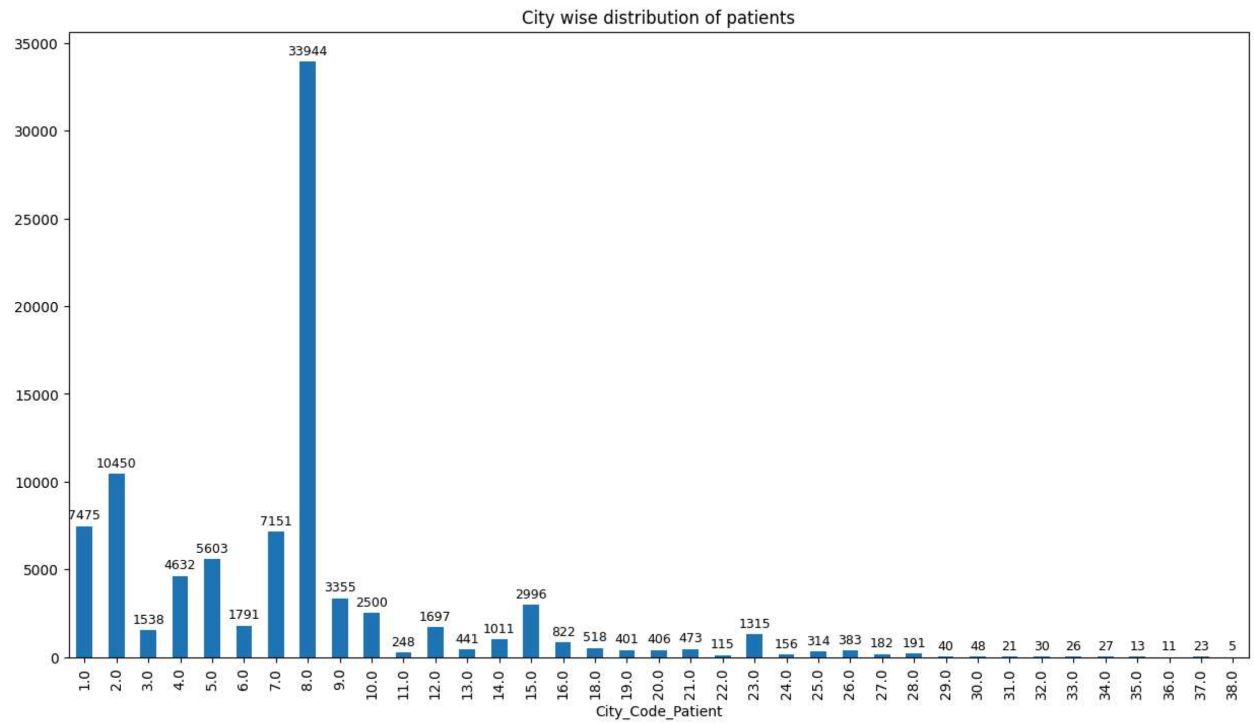
- The patients having the age between 30 and 50 contribute to 40% of the entire data.
- Irrespective of the age group gynecology department has the highest number of patients with 249486 out of 318438 which is 78% of the whole data.
- The management should focus making sure that all required resources are available for the department to cope up with the demand.

Patient city wise analysis

In [43]:
```
ptcountcitywise = df.groupby('City_Code_Patient').patientid.nunique()
```

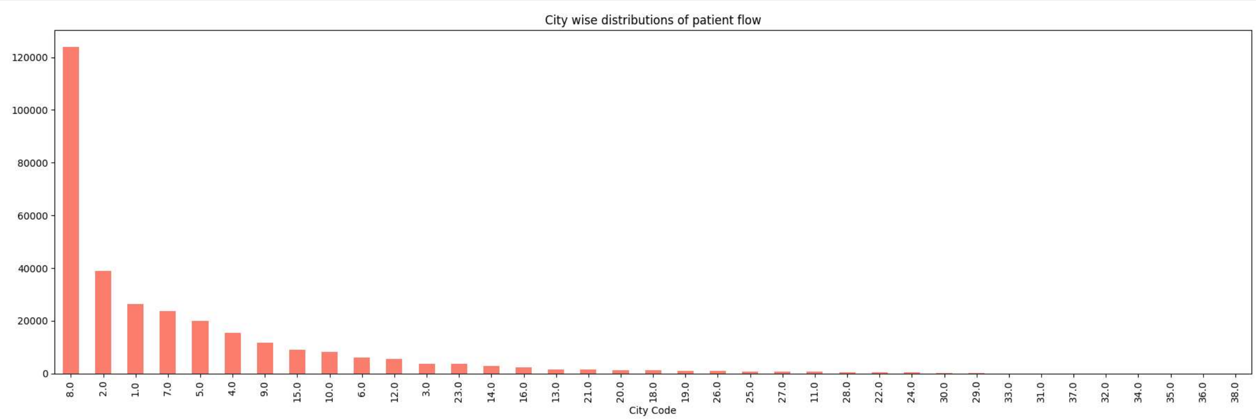
In [99]:

```
plt.figure(figsize=(15,8))
ax = ptcountcitywise.plot(kind='bar')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.title('City wise distribution of patients')
plt.show()
```



In [104]:

```
plt.figure(figsize=(18, 6))
df['City_Code_Patient'].value_counts().plot(kind='bar', color='salmon')
plt.title('City wise distributions of patient flow')
plt.xlabel('City Code')
plt.tight_layout()
plt.show()
```

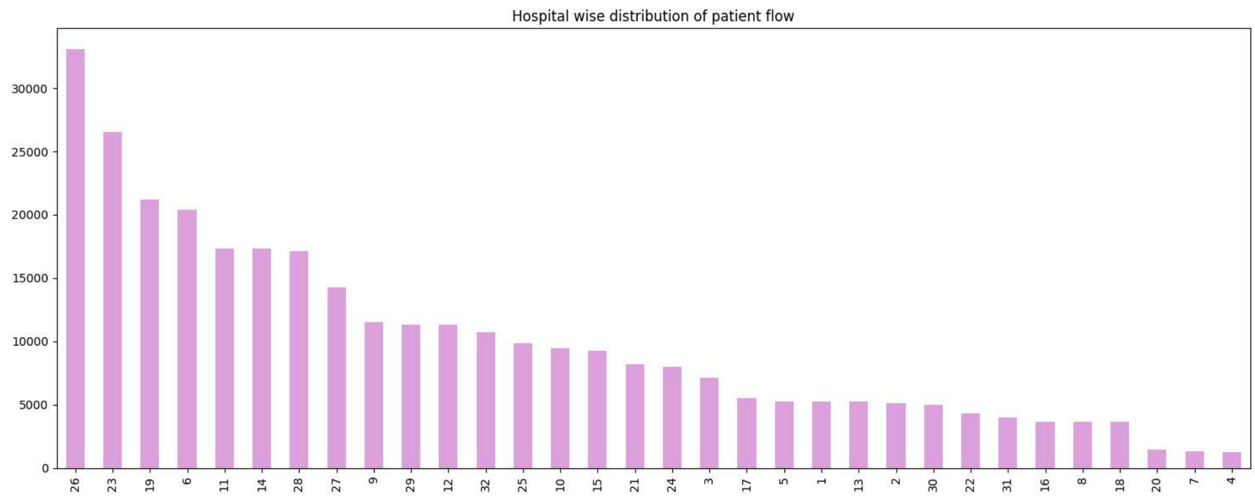


In [71]:
```
print('\nTop five cities with highest patient count')
ptcountcitywise.sort_values(axis='index', ascending=False).head(5)
```

```
Top five cities with highest patient count
```

Out[71]:
```
City_Code_Patient
8.0    33944
2.0    10450
1.0     7475
7.0     7151
5.0     5603
Name: patientid, dtype: int64
```

In [187]:
```
plt.figure(figsize=(15,6))
df['Hospital_code'].value_counts().plot(kind='bar', color='plum')
plt.title('Hospital wise distribution of patient flow')
plt.tight_layout()
plt.show()
```



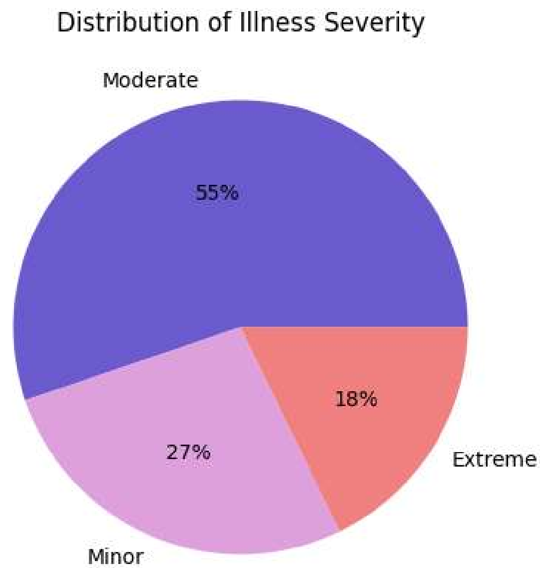
Insight:

- The city with code 8 has the highest contribution to the patient count as well as the patient flow.
- Out of all the hospital the hospital with code 26 has the highest patinet flow and code 4 has the lowest.

Analyzing Illness Severity

In [193]:

```
plt.figure(figsize=(8, 5))
df['Severity of Illness'].value_counts().plot(kind='pie', autopct='%1.0f%%', colors=['slateblue', 'plum', 'ligh
plt.title('Distribution of Illness Severity')
plt.ylabel('')
plt.show()
```



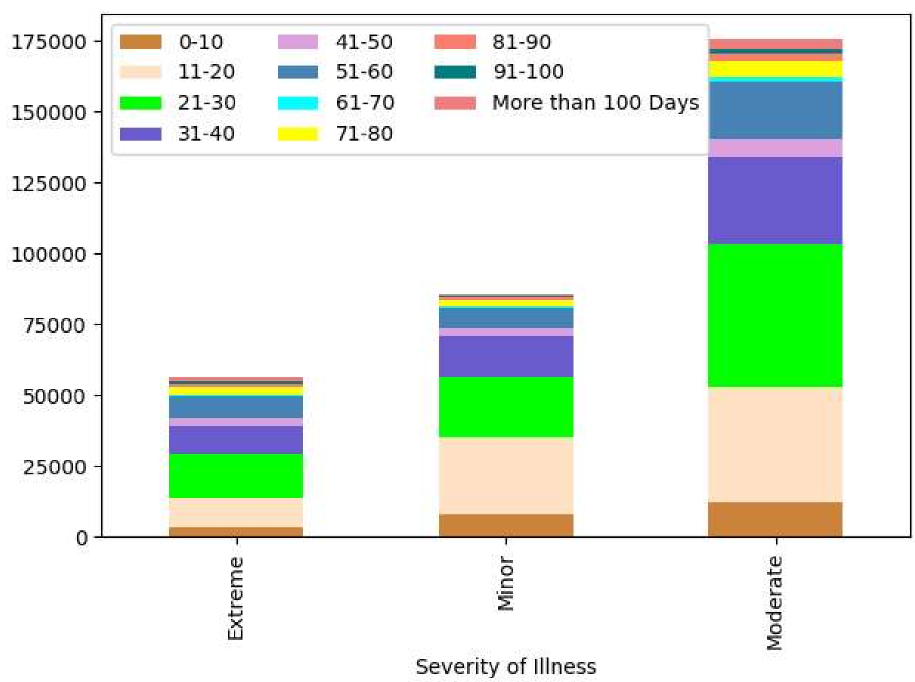
In [201]:

```
ss = pd.crosstab(df['Severity of Illness'], df['Stay'])
```

In [203]:

```
plt.figure(figsize=(15,8))
ss.plot(kind='bar', stacked=True, color=['peru', 'bisque', 'lime', 'slateblue', 'plum', 'steelblue', 'aqua', 'y
plt.legend(ncols=3, loc='upper left')
plt.tight_layout()
plt.show()
```

<Figure size 1500x800 with 0 Axes>



In [233]:
```
pd.crosstab(df['Severity of Illness'], df['Stay'], normalize=True, margins=True)
```

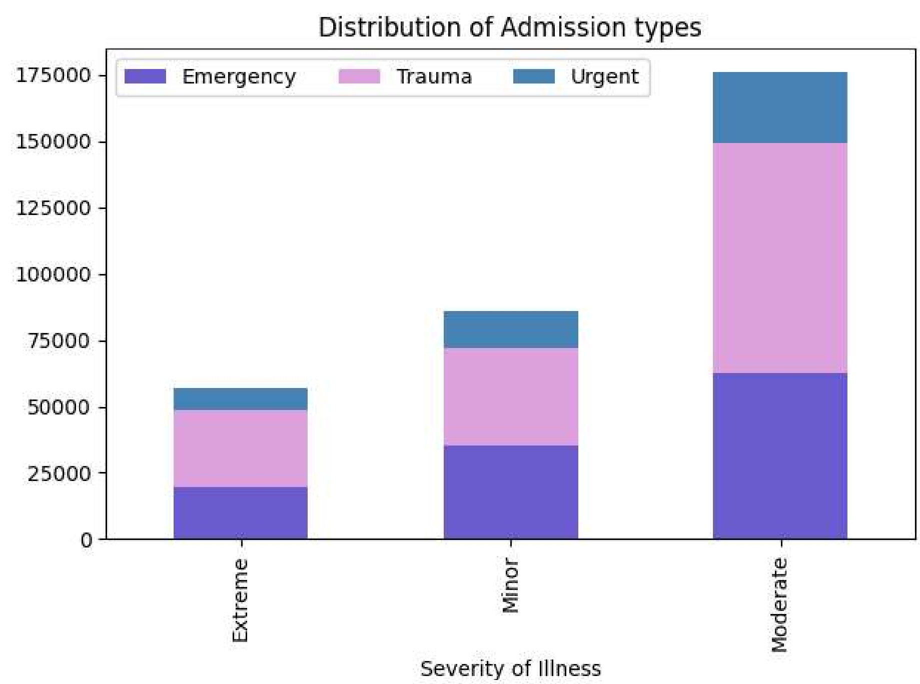
Out[233]:

Stay	0-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	81-90	91-100	More than 100 Days	All
Severity of Illness												
Extreme	0.010674	0.033030	0.048681	0.031673	0.007383	0.024422	0.002032	0.008086	0.003495	0.002528	0.006124	0.178129
Minor	0.024702	0.085043	0.067627	0.045368	0.009421	0.022384	0.001630	0.006055	0.003093	0.001335	0.003008	0.269666
Moderate	0.038749	0.127309	0.158442	0.096176	0.020073	0.063161	0.004955	0.018060	0.008605	0.004820	0.011855	0.552205
All	0.074124	0.245382	0.274751	0.173217	0.036877	0.109968	0.008617	0.032201	0.015193	0.008683	0.020987	1.000000

In [212]:
```
st = pd.crosstab(df['Severity of Illness'], df['Type of Admission'])
```

In [222]:
```
plt.figure(figsize=(15,8))
st.plot(kind='bar', stacked=True, color=['slateblue', 'plum', 'steelblue',])
plt.legend(ncols=3, loc='upper left')
plt.title('Distribution of Admission types')
plt.tight_layout()
plt.show()
```

<Figure size 1500x800 with 0 Axes>



In [223]:
```
pd.crosstab(df['Severity of Illness'], df['Type of Admission'], margins=True)
```

Out[223]:

Type of Admission	Emergency	Trauma	Urgent	All
Severity of Illness				
Extreme	19844	28837	8042	56723
Minor	35356	36800	13716	85872
Moderate	62476	86624	26743	175843
All	117676	152261	48501	318438

Insights:

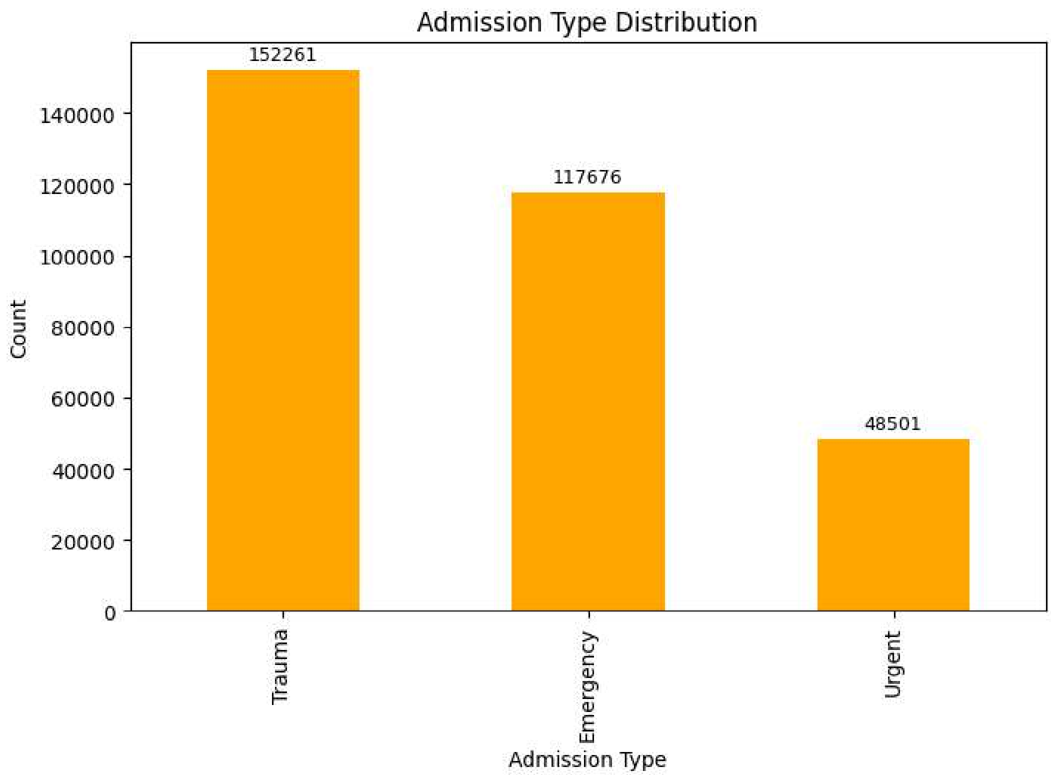
- 55% of the cases admitted to the hospitals are moderate cases.
- The admission type Trauma contributes to 48% of the total cases admitted out of which 56% are moderate.
- The urgent admission type has the least number of cases which contibutes only 15% of all the cases admitted.
- 27% of the patients admitted stay in a rage of 21-30 days in which more than 50% belongs to the moderate illness type.

- Approximately 69% of the patients stay in the hospital ranging from 11 to 40 days.

Admission Types Analysis:

In [237]:

```
plt.figure(figsize=(8, 5))
ax = df['Type of Admission'].value_counts().plot(kind='bar', color='orange')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.title('Admission Type Distribution')
plt.xlabel('Admission Type')
plt.ylabel('Count')
plt.show()
```



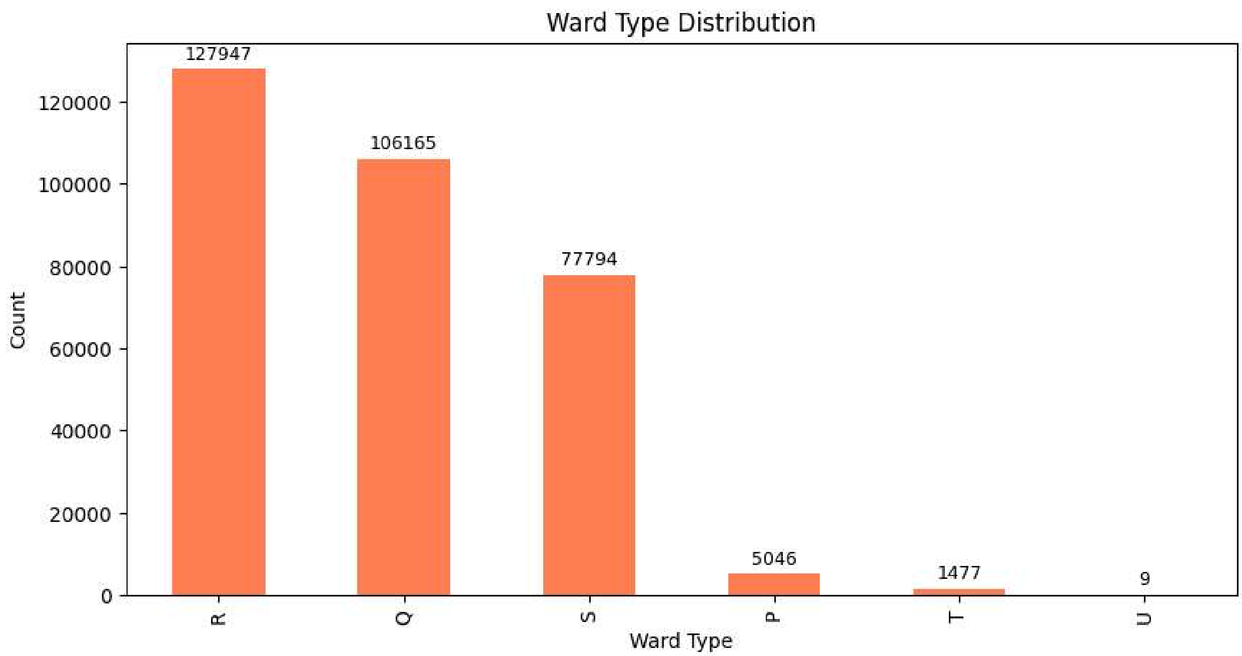
Insights:

- The most of the cases admitted to the hospital belongs to the type Trauma and emergency.

Ward Utilization Examination:

In [247]:

```
plt.figure(figsize=(10,5))
ax = df['Ward_Type'].value_counts().plot(kind='bar', color='coral')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.title('Ward Type Distribution')
plt.xlabel('Ward Type')
plt.ylabel('Count')
plt.show()
```



Insights:

- The ward types R, Q and S are used widely where as the types P, T and U are under utilized.
- The trend shows that the patients prefer to use the types R, Q and S.
- The hospital management can think about converting the P, T and U types to those preferred by the patients.

Hospital Utilization Assessment

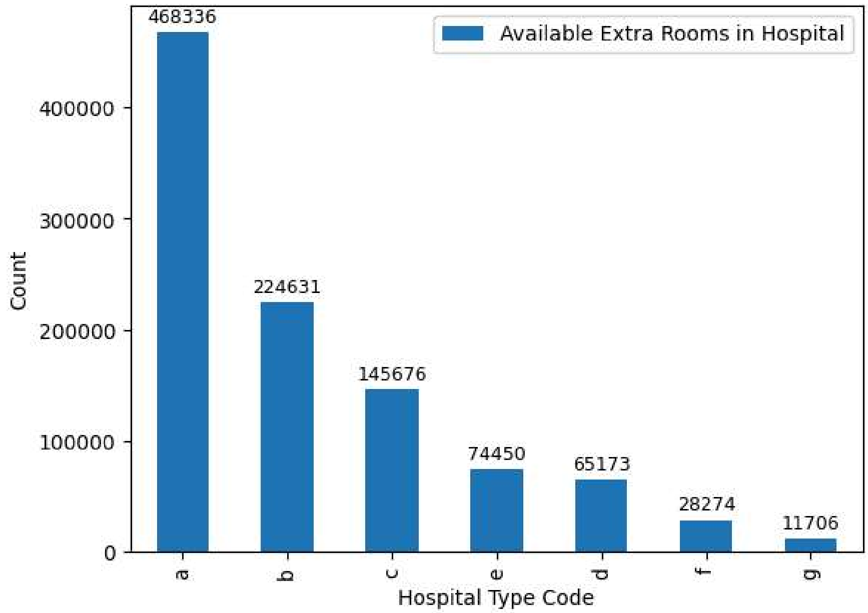
In [287]:

```
ha = df.groupby(['Hospital_type_code']).agg({'Available Extra Rooms in Hospital': 'sum'}).reset_index().sort_va
ha.drop('index', axis=1, inplace=True)
```

In [300]:

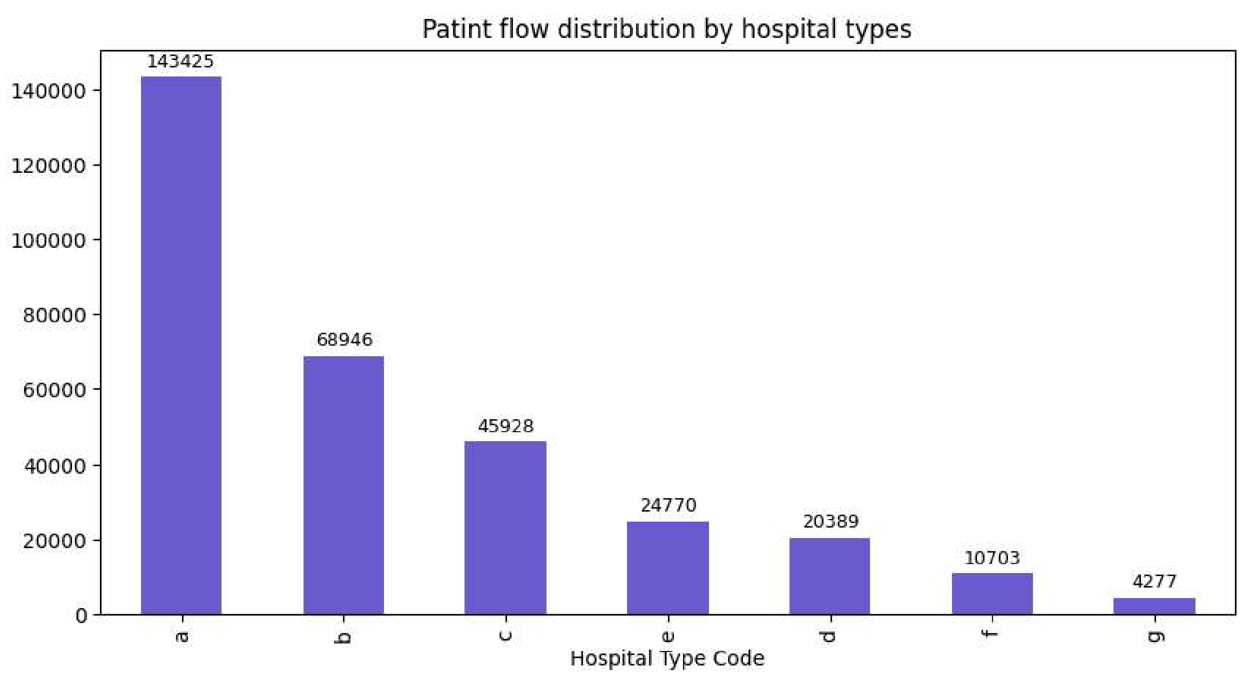
```
plt.figure(figsize=(8,5))
ax = ha.plot(kind='bar', x='Hospital_type_code')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.xlabel('Hospital Type Code')
plt.ylabel('Count')
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```



In [292]:

```
plt.figure(figsize=(10,5))
ax = df['Hospital_type_code'].value_counts().plot(kind='bar', color='slateblue')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.title('Patint flow distribution by hospital types')
plt.xlabel('Hospital Type Code')
plt.show()
```



Insights:

- The distribution of availability of the rooms is exactly according to the intensity of the patient flow in the corresponding hospital type.

Overall Insights:

- Missing values are present in the Bed Grade and City Code of the Patient columns, but all patients' city codes were eventually collected during their hospital visits.
- Patients aged between 30 and 50 constitute 40% of the entire dataset.
- Gynecology department has the highest patient count, accounting for 78% of the total data.
- City with code 8 has the highest contribution to patient count and flow.
- Hospital code 26 has the highest patient flow, while code 4 has the lowest.
- Moderate cases comprise 55% of hospital admissions, with Trauma being the most common admission type (48% of total cases).
- Patients admitted for Trauma have a moderate illness severity in 56% of cases.
- A significant portion (27%) of admitted patients stay for 21-30 days, with over 50% having moderate illness severity.
- Approximately 69% of patients stay in the hospital for 11-40 days.
- Wards R, Q, and S are widely used, while P, T, and U are underutilized.
- Patients tend to prefer wards R, Q, and S over others.

Recommendations:

- Ensure availability of resources in the Gynecology department to meet the high demand.
- Focus on improving data collection processes to minimize missing values in the dataset.
- Allocate resources according to patient flow trends, with extra attention to hospitals in cities with code 8 and hospital code 26.
- Enhance services and facilities in wards R, Q, and S to meet patient preferences, and consider converting underutilized wards (P, T, and U) to preferred types.
- Tailor resource allocation and capacity planning based on the distribution of patient stays and admission types.
- Implement strategies to reduce patient stays by improving treatment efficiency and care delivery, especially for moderate cases.
- Develop targeted marketing or outreach efforts to educate patients about available services in underutilized wards.
- Regularly review and adjust resource allocation strategies based on evolving patient demographics and hospital utilization patterns.