

```
In [17]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [2]: df = pd.read_csv(r'C:\Users\nikde\Downloads\hospital_readmission.csv')
```

```
In [3]: df.head(5)
```

Out[3]:

	encounter_id	patient_nbr	race	gender	age	weight	admission_type_id	discharge_disposition_id	admission_source_
0	2278392	8222157	Caucasian	Female	[0-10)	?	6	25	
1	149190	55629189	Caucasian	Female	[10-20)	?	1	1	
2	64410	86047875	AfricanAmerican	Female	[20-30)	?	1	1	
3	500364	82442376	Caucasian	Male	[30-40)	?	1	1	
4	16680	42519267	Caucasian	Male	[40-50)	?	1	1	

5 rows × 50 columns



```
In [4]: df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101766 entries, 0 to 101765
Data columns (total 50 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   encounter_id                          101766 non-null  int64
1   patient_nbr                           101766 non-null  int64
2   race                                  101766 non-null  object
3   gender                                 101766 non-null  object
4   age                                    101766 non-null  object
5   weight                                101766 non-null  object
6   admission_type_id                     101766 non-null  int64
7   discharge_disposition_id              101766 non-null  int64
8   admission_source_id                   101766 non-null  int64
9   time_in_hospital                      101766 non-null  int64
10  payer_code                             101766 non-null  object
11  medical_specialty                     101766 non-null  object
12  num_lab_procedures                    101766 non-null  int64
13  num_procedures                         101766 non-null  int64
14  num_medications                       101766 non-null  int64
15  number_outpatient                      101766 non-null  int64
16  number_emergency                       101766 non-null  int64
17  number_inpatient                      101766 non-null  int64
18  diag_1                                101766 non-null  object
19  diag_2                                101766 non-null  object
20  diag_3                                101766 non-null  object
21  number_diagnoses                       101766 non-null  int64
22  max_glu_serum                          5346 non-null   object
23  A1Cresult                              17018 non-null  object
24  metformin                              101766 non-null  object
25  repaglinide                            101766 non-null  object
26  nateglinide                            101766 non-null  object
27  chlorpropamide                         101766 non-null  object
28  glimepiride                             101766 non-null  object
29  acetohexamide                         101766 non-null  object
30  glipizide                               101766 non-null  object
31  glyburide                               101766 non-null  object
32  tolbutamide                             101766 non-null  object
33  pioglitazone                           101766 non-null  object
34  rosiglitazone                          101766 non-null  object
35  acarbose                               101766 non-null  object
36  miglitol                               101766 non-null  object
37  troglitazone                           101766 non-null  object
38  tolazamide                             101766 non-null  object
39  examide                                101766 non-null  object
40  citoglipton                            101766 non-null  object
41  insulin                                101766 non-null  object
42  glyburide-metformin                    101766 non-null  object
43  glipizide-metformin                    101766 non-null  object
44  glimepiride-pioglitazone                101766 non-null  object
45  metformin-rosiglitazone                 101766 non-null  object
46  metformin-pioglitazone                  101766 non-null  object
47  change                                  101766 non-null  object
48  diabetesMed                             101766 non-null  object
49  readmitted                             101766 non-null  object
dtypes: int64(13), object(37)
memory usage: 38.8+ MB

```

```
In [5]: df.describe()
```

```

Out[5]:

```

	encounter_id	patient_nbr	admission_type_id	discharge_disposition_id	admission_source_id	time_in_hospital	num_lab_p
count	1.017660e+05	1.017660e+05	101766.000000	101766.000000	101766.000000	101766.000000	1017
mean	1.652016e+08	5.433040e+07	2.024006	3.715642	5.754437	4.395987	
std	1.026403e+08	3.869636e+07	1.445403	5.280166	4.064081	2.985108	
min	1.252200e+04	1.350000e+02	1.000000	1.000000	1.000000	1.000000	
25%	8.496119e+07	2.341322e+07	1.000000	1.000000	1.000000	2.000000	
50%	1.523890e+08	4.550514e+07	1.000000	1.000000	7.000000	4.000000	
75%	2.302709e+08	8.754595e+07	3.000000	4.000000	7.000000	6.000000	
max	4.438672e+08	1.895026e+08	8.000000	28.000000	25.000000	14.000000	1

```

In [6]: readmitted_counts = df['readmitted'].value_counts(normalize=True)
readmitted_counts
plt.figure(figsize=(6, 6))
plt.pie(readmitted_counts.values,
        labels=readmitted_counts.index,
        autopct='%1.1f%%',

```

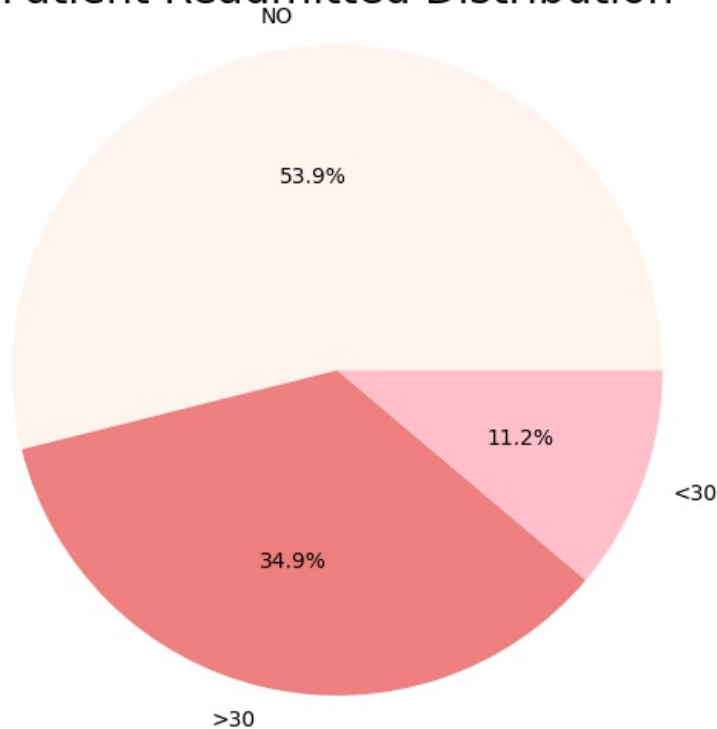
```

colors=['seashell', 'lightcoral', 'pink'])

plt.title('Patient Readmitted Distribution', size = 20)
plt.axis('equal')
plt.show()

```

Patient Readmitted Distribution



So, here we get clear idea that 46.1 percent of patient get readmitted and out of readmitted patients 11.2 % get readmitted within a month and rest 34.9 % get readmitted but after a month.

Ques 2 :- How does patient age impact readmission rates ??

What is the distribution of patients across different medical specialties?

```

In [7]: Speciality_counts = df['medical_specialty'].value_counts(normalize=True)
Speciality_counts

```

```

Out[7]: medical_specialty
not known                0.490822
InternalMedicine         0.143810
Emergency/Trauma        0.074337
Family/GeneralPractice  0.073109
Cardiology               0.052591
...
SportsMedicine          0.000010
Speech                  0.000010
Perinatology            0.000010
Neurophysiology         0.000010
Pediatrics-InfectiousDiseases 0.000010
Name: proportion, Length: 73, dtype: float64

```

How does patient age impact readmission rates?

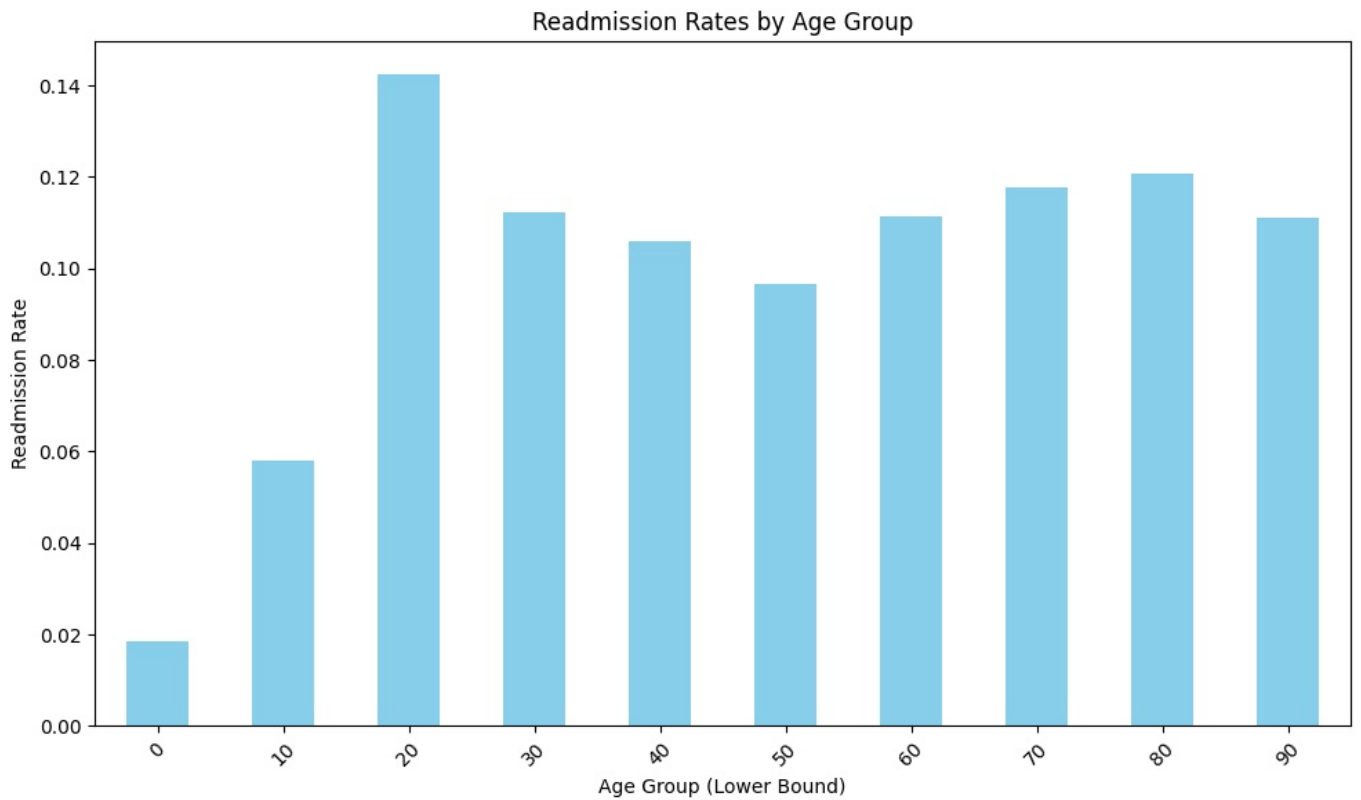
```

In [9]: # Step 1: Data cleaning (example)
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 0, 'NO': 0}) # Encode readmission as 1 (yes) and
df['age'] = df['age'].str.strip('[]').str.split('-').str[0].astype(int) # Convert age ranges to numerical lower

# Step 2: Group by age ranges
age_groups = df.groupby('age')['readmitted'].mean() # Calculate mean readmission rate by age group

# Step 3: Plotting
plt.figure(figsize=(10, 6))
age_groups.plot(kind='bar', color='skyblue')
plt.title('Readmission Rates by Age Group')
plt.xlabel('Age Group (Lower Bound)')
plt.ylabel('Readmission Rate')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

```



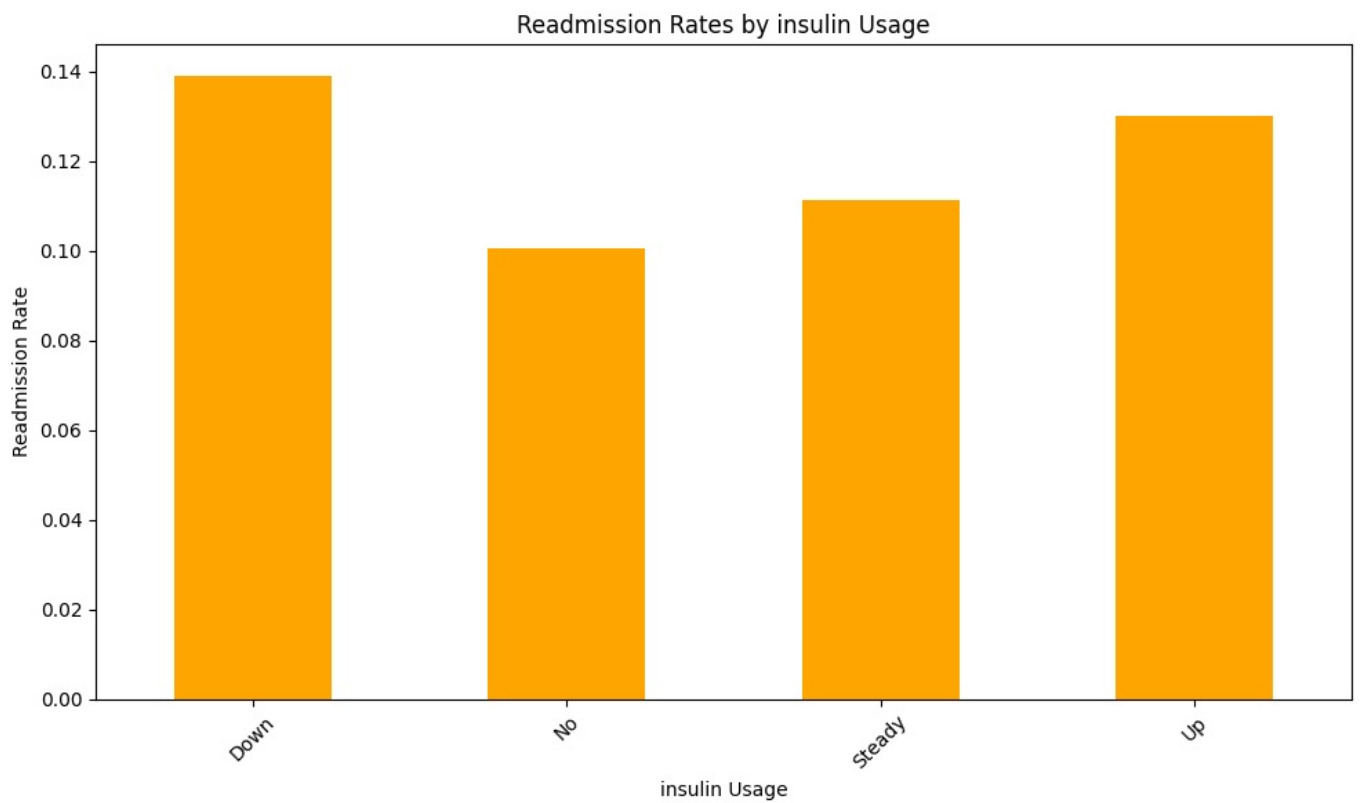
```
In [22]: # Step 1: Preprocessing
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 1, 'NO': 0}) # Encode readmitted as 1 (yes) and 0 (no)

# Step 2: Focus on procedure and medication columns
procedure_medication_cols = [
    'num_lab_procedures', 'num_procedures', 'num_medications',
    'metformin', 'repaglinide', 'nateglinide', 'chlorpropamide',
    'glimepiride', 'acetoheaxamide', 'glipizide', 'glyburide',
    'tolbutamide', 'pioglitazone', 'rosiglitazone', 'acarbose',
    'miglitol', 'troglitazone', 'tolazamide', 'insulin'
]

# Step 3: Aggregate readmission rates
results = {}
for col in procedure_medication_cols:
    if df[col].dtype == 'object': # If categorical (e.g., medications)
        rates = df.groupby(col)['readmitted'].mean() # Calculate mean readmission rate per category
        results[col] = rates
    else: # If numerical (e.g., counts of procedures)
        correlation = df[[col, 'readmitted']].corr().iloc[0, 1] # Correlation with readmission
        results[col] = correlation

# Step 4: Visualization (Example for a medication column like insulin)
medication = 'insulin'
readmission_rates = results[medication]

plt.figure(figsize=(10, 6))
readmission_rates.plot(kind='bar', color='orange')
plt.title(f'Readmission Rates by {medication} Usage')
plt.xlabel(f'{medication} Usage')
plt.ylabel('Readmission Rate')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



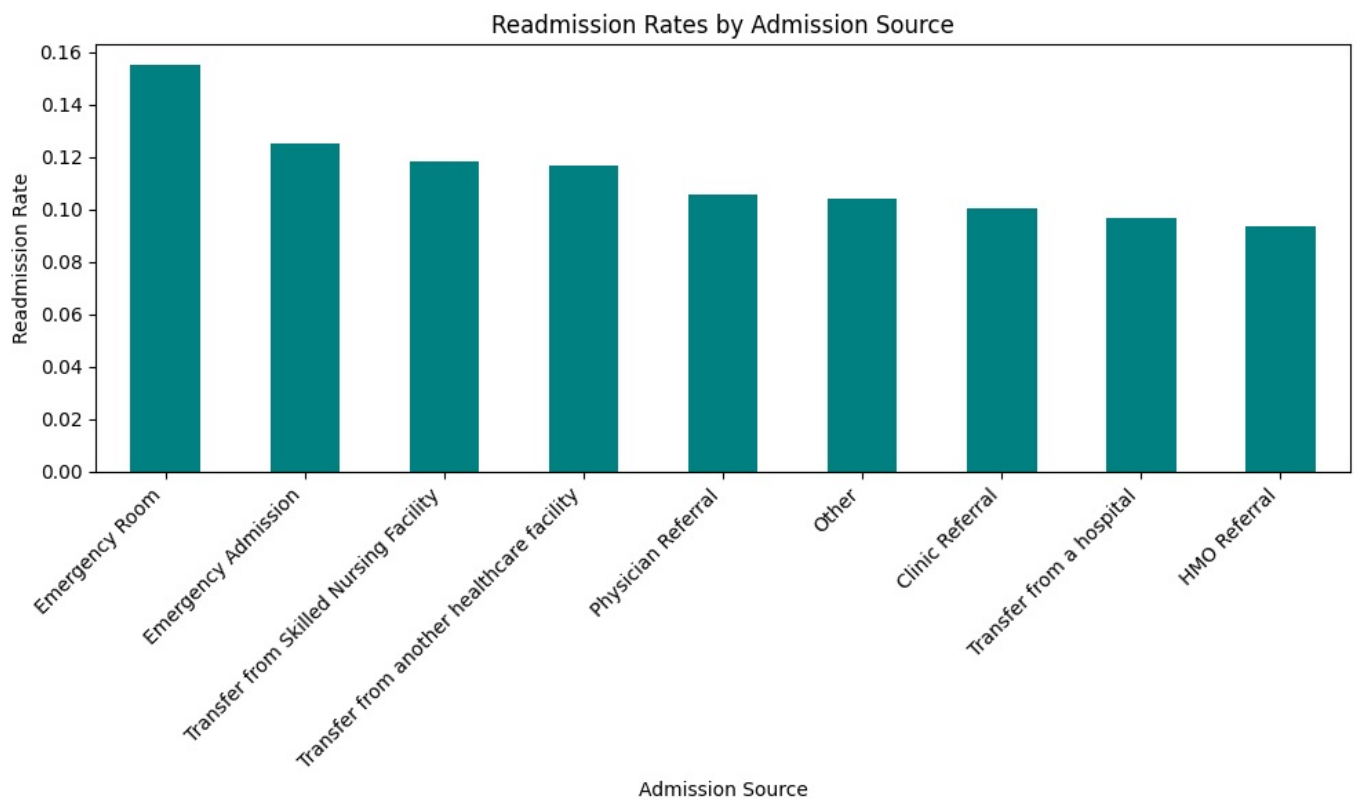
```
In [13]: # Step 1: Preprocess the data
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 1, 'NO': 0}) # Encode readmitted as 1 (yes) and 0 (no)

# Optional: Map admission_source_id to descriptive labels if a mapping is available
admission_source_mapping = {
    1: 'Physician Referral', 2: 'Clinic Referral', 3: 'Emergency Room',
    4: 'Transfer from a hospital', 5: 'Transfer from Skilled Nursing Facility',
    6: 'HMO Referral', 7: 'Transfer from another healthcare facility',
    8: 'Emergency Admission', 9: 'Other'
}
df['admission_source'] = df['admission_source_id'].map(admission_source_mapping)

# Step 2: Group by admission source and calculate readmission rates
readmission_rates = df.groupby('admission_source')['readmitted'].mean()

# Step 3: Visualize the results
plt.figure(figsize=(10, 6))
readmission_rates.sort_values(ascending=False).plot(kind='bar', color='teal')
plt.title('Readmission Rates by Admission Source')
plt.xlabel('Admission Source')
plt.ylabel('Readmission Rate')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Display the readmission rates for reference
print(readmission_rates.sort_values(ascending=False))
```



admission_source	
Emergency Room	0.155080
Emergency Admission	0.125000
Transfer from Skilled Nursing Facility	0.118129
Transfer from another healthcare facility	0.116882
Physician Referral	0.105868
Other	0.104000
Clinic Referral	0.100543
Transfer from a hospital	0.096956
HMO Referral	0.093640

Name: readmitted, dtype: float64

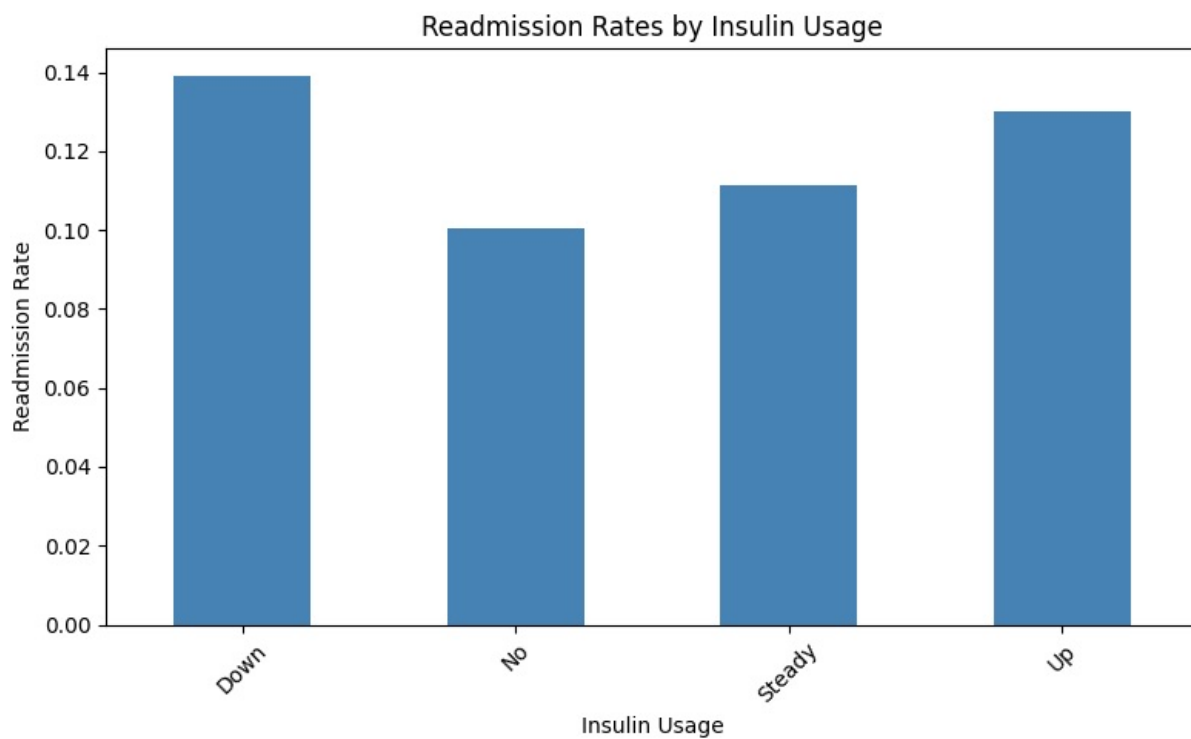
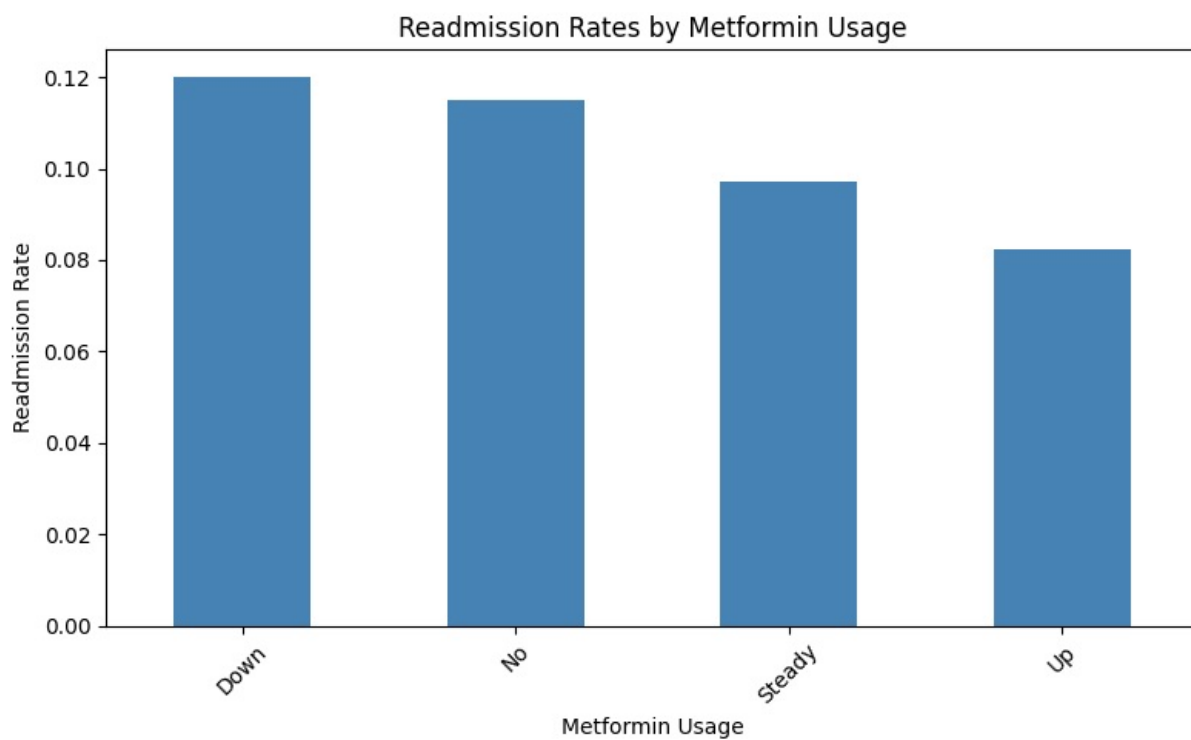
```
In [15]: # Step 1: Preprocessing
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 1, 'NO': 0}) # Encode readmitted as 1 or 0

# List of medication columns to analyze
medications = ['metformin', 'insulin', 'glipizide', 'glyburide', 'pioglitazone']

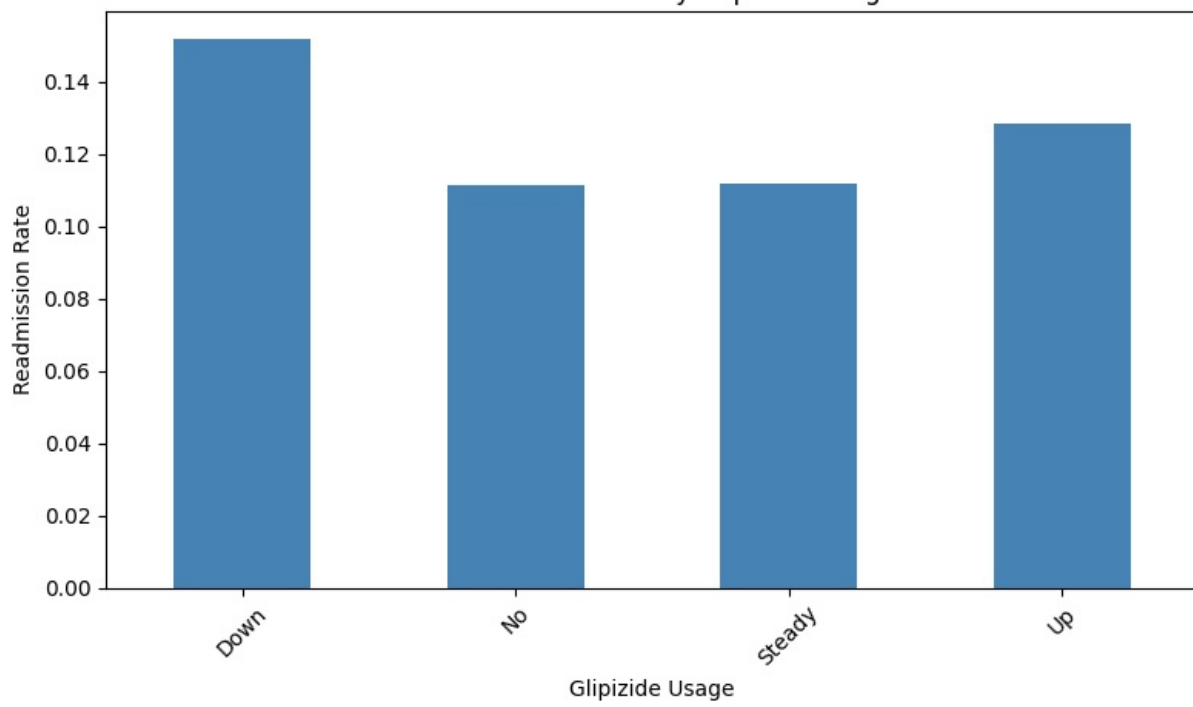
# Step 2: Calculate readmission rates for each medication
medication_effectiveness = {}
for med in medications:
    rates = df.groupby(med)['readmitted'].mean() # Mean readmission rate by usage category
    medication_effectiveness[med] = rates

# Step 3: Visualization
for med, rates in medication_effectiveness.items():
    plt.figure(figsize=(8, 5))
    rates.plot(kind='bar', color='steelblue')
    plt.title(f'Readmission Rates by {med.capitalize()} Usage')
    plt.xlabel(f'{med.capitalize()} Usage')
    plt.ylabel('Readmission Rate')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

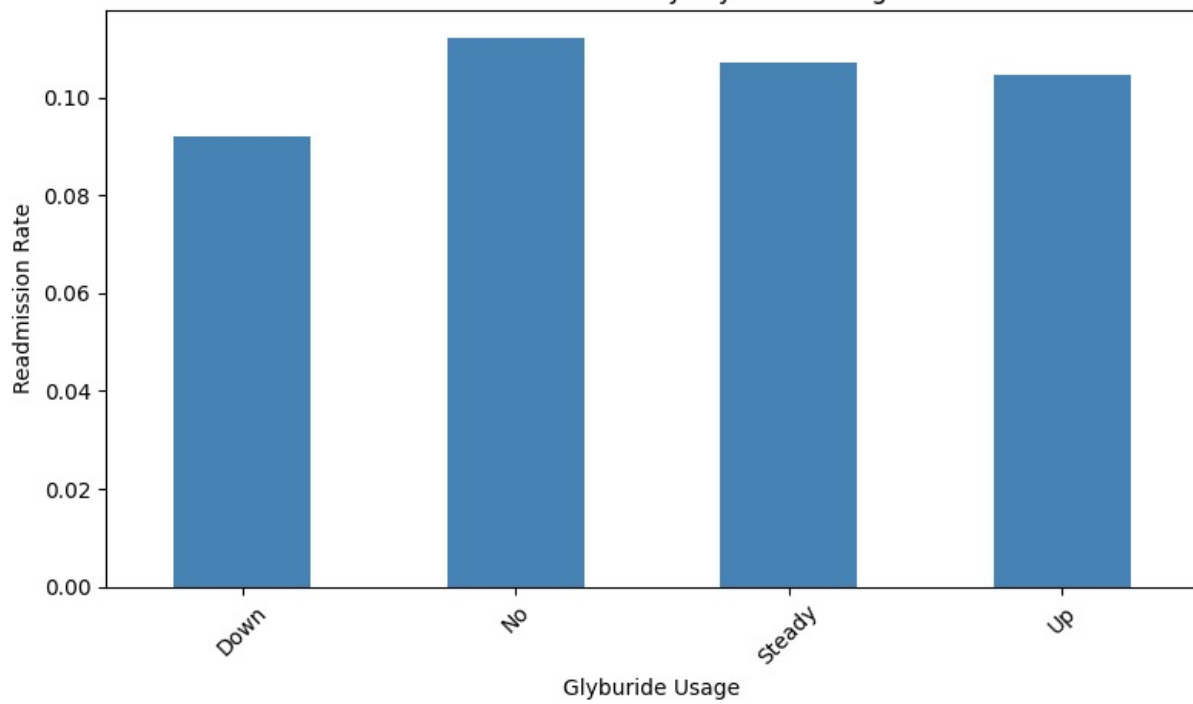
# Step 4: Summary Table
summary_table = pd.DataFrame(medication_effectiveness).T
summary_table.columns = ['No', 'Steady', 'Up', 'Down'] # Adjust based on actual categories in the dataset
print("Medication Effectiveness Summary:")
print(summary_table)
```

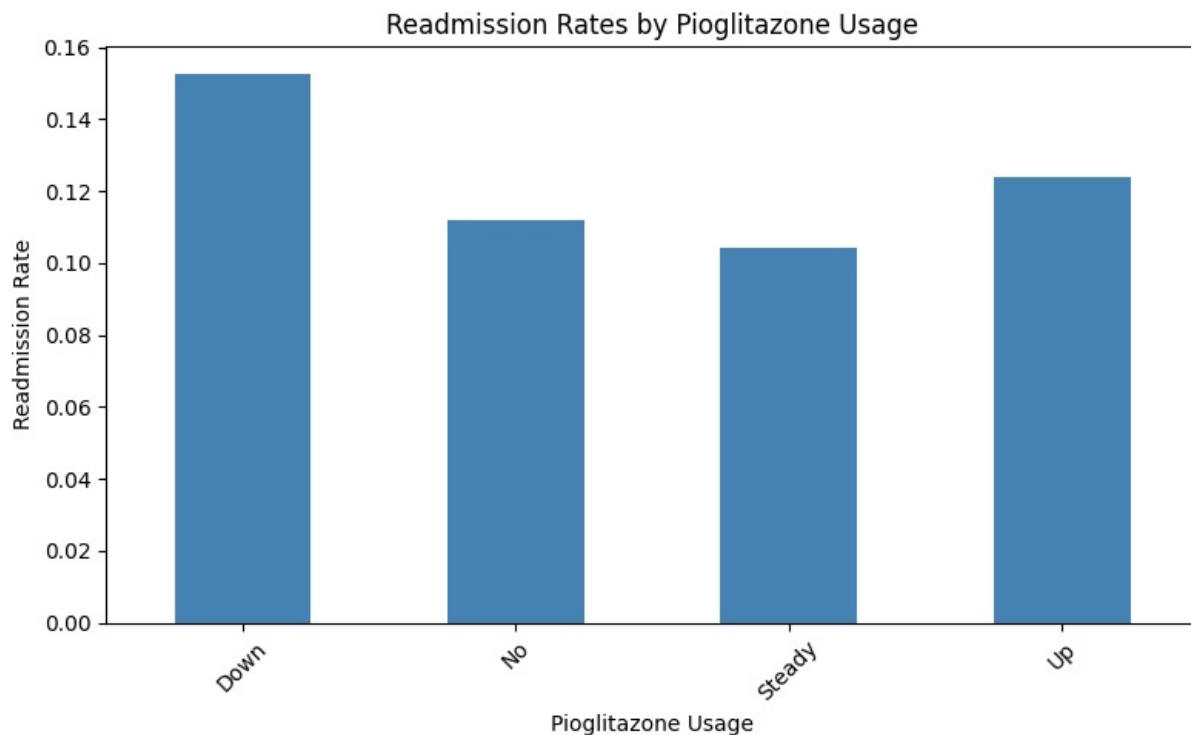


Readmission Rates by Glipizide Usage



Readmission Rates by Glyburide Usage





Medication Effectiveness Summary:

	No	Steady	Up	Down
metformin	0.120000	0.115165	0.097133	0.082474
insulin	0.138975	0.100374	0.111284	0.129905
glipizide	0.151786	0.111192	0.111659	0.128571
glyburide	0.092199	0.112220	0.107289	0.104680
pioglitazone	0.152542	0.112063	0.104214	0.123932

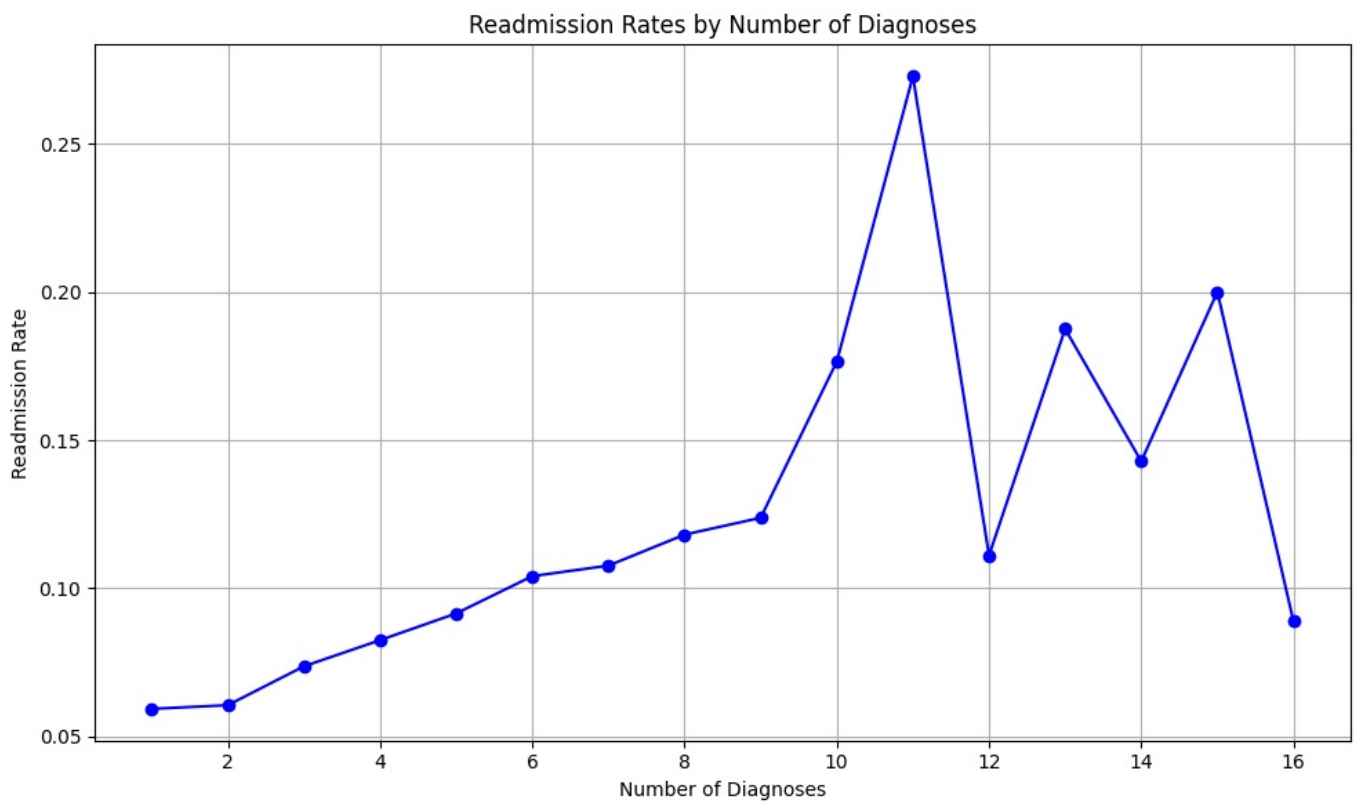
```
In [18]: # Step 1: Preprocessing
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 1, 'NO': 0}) # Encode readmitted as 1 or 0

# Step 2: Calculate readmission rates by number of diagnoses
diagnosis_readmission_rates = df.groupby('number_diagnoses')['readmitted'].mean()

# Step 3: Visualization
plt.figure(figsize=(10, 6))
plt.plot(diagnosis_readmission_rates.index, diagnosis_readmission_rates.values, marker='o', color='blue')
plt.title('Readmission Rates by Number of Diagnoses')
plt.xlabel('Number of Diagnoses')
plt.ylabel('Readmission Rate')
plt.grid(True)
plt.tight_layout()
plt.show()

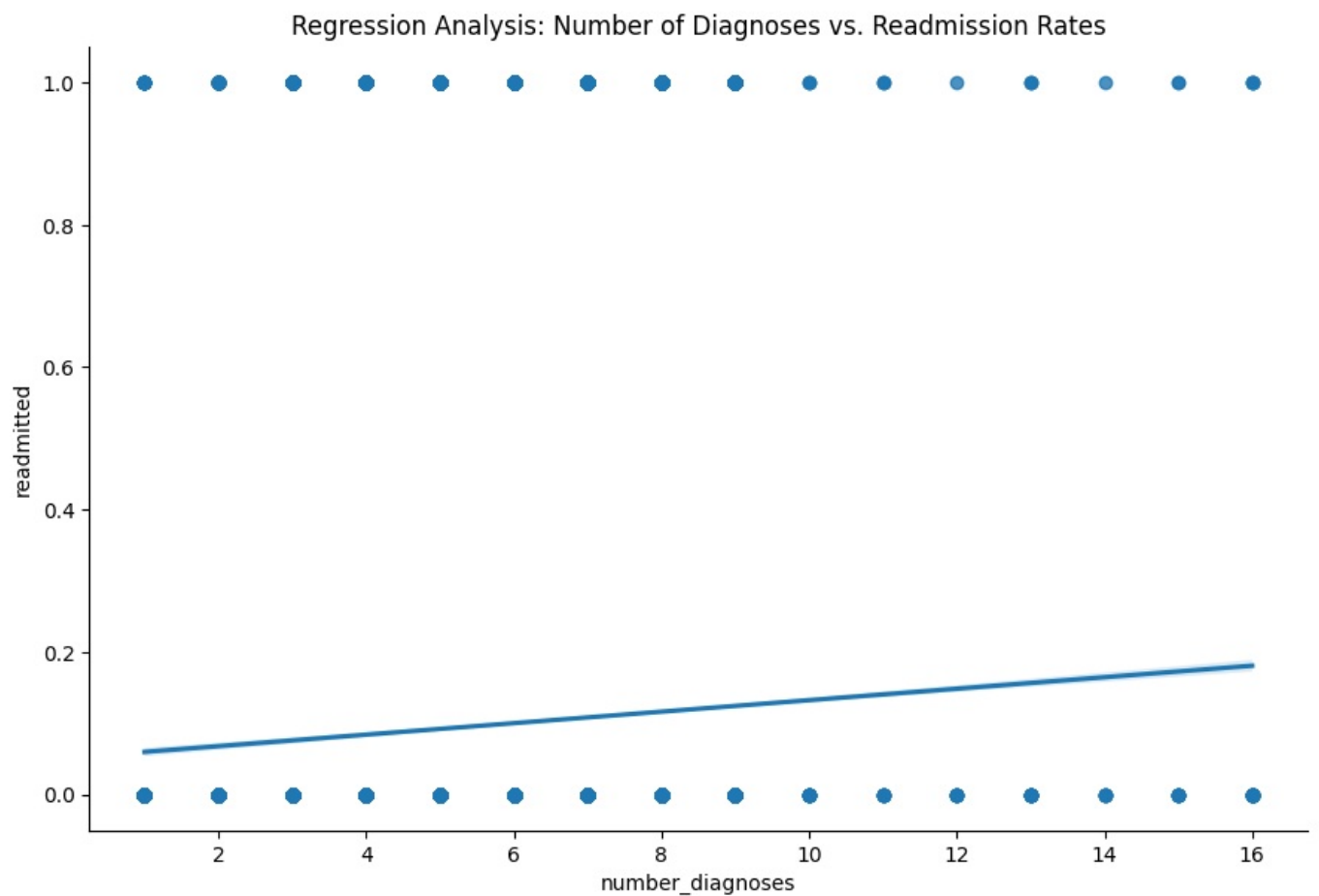
# Step 4: Correlation analysis
correlation = df[['number_diagnoses', 'readmitted']].corr().iloc[0, 1]
print(f"Correlation between number of diagnoses and readmission rates: {correlation:.2f}")

# Optional: Regression analysis
sns.lmplot(x='number_diagnoses', y='readmitted', data=df, height=6, aspect=1.5)
plt.title('Regression Analysis: Number of Diagnoses vs. Readmission Rates')
plt.show()
```



Correlation between number of diagnoses and readmission rates: 0.05

C:\Users\nikde\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has changed to tight
 self.figure.tight_layout(*args, **kwargs)



```
In [20]: # Step 1: Preprocessing
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 1, 'NO': 0}) # Encode readmitted as 1 or 0

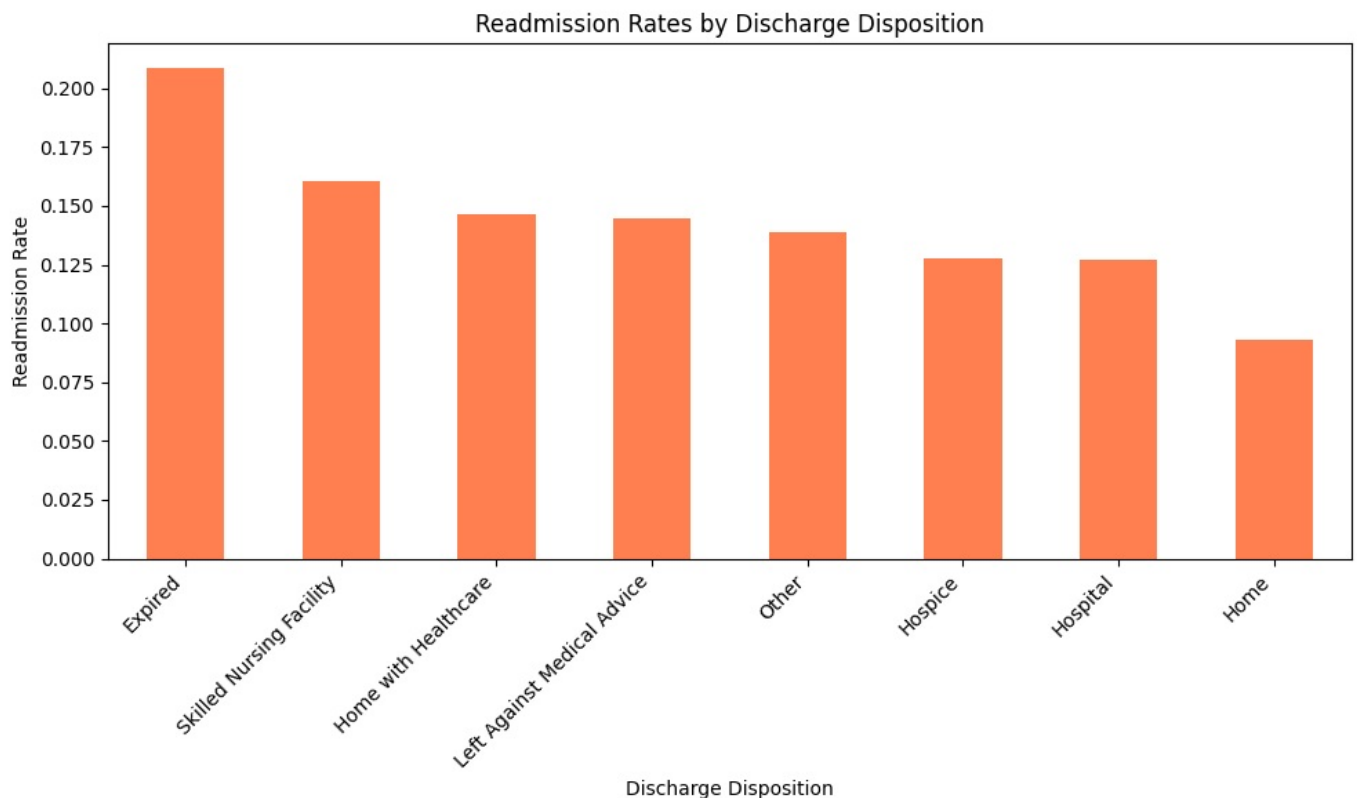
# Optional: Map discharge_disposition_id to descriptive labels
discharge_mapping = {
    1: 'Home', 2: 'Skilled Nursing Facility', 3: 'Home with Healthcare',
    4: 'Hospice', 5: 'Expired', 6: 'Hospital', 7: 'Left Against Medical Advice',
    8: 'Other'
}
df['discharge_disposition'] = df['discharge_disposition_id'].map(discharge_mapping)
```

```
# Step 2: Calculate readmission rates by discharge disposition
readmission_rates = df.groupby('discharge_disposition')['readmitted'].mean()

# Step 3: Visualization
plt.figure(figsize=(10, 6))
readmission_rates.sort_values(ascending=False).plot(kind='bar', color='coral')
plt.title('Readmission Rates by Discharge Disposition')
plt.xlabel('Discharge Disposition')
plt.ylabel('Readmission Rate')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Step 4: Correlation Analysis
# Assuming discharge_disposition_id is numeric, calculate correlation
correlation = df[['discharge_disposition_id', 'readmitted']].corr().iloc[0, 1]
print(f"Correlation between discharge disposition ID and readmission rates: {correlation:.2f}")

# Print the readmission rates for reference
print("Readmission Rates by Discharge Disposition:")
print(readmission_rates.sort_values(ascending=False))
```



Correlation between discharge disposition ID and readmission rates: 0.05

Readmission Rates by Discharge Disposition:

discharge_disposition	
Expired	0.208615
Skilled Nursing Facility	0.160714
Home with Healthcare	0.146625
Left Against Medical Advice	0.144462
Other	0.138889
Hospice	0.127607
Hospital	0.126957
Home	0.093004

Name: readmitted, dtype: float64

```
In [24]: # Step 1: Preprocessing
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 1, 'NO': 0}) # Encode readmitted as 1 or 0

# Step 2: Group by readmission status and calculate summary statistics
summary_stats = df.groupby('readmitted')['time_in_hospital'].describe()

# Display summary statistics
print("Summary Statistics for Length of Stay by Readmission Status:")
print(summary_stats)

# Step 3: Visualization
plt.figure(figsize=(10, 6))
sns.boxplot(x='readmitted', y='time_in_hospital', data=df, palette='Set2')
plt.title('Length of Stay by Readmission Status')
plt.xlabel('Readmission Status (0 = Not Readmitted, 1 = Readmitted)')
plt.ylabel('Length of Stay (days)')
plt.xticks([0, 1], ['Not Readmitted', 'Readmitted'])
```

```
plt.grid(axis='y')
plt.tight_layout()
plt.show()

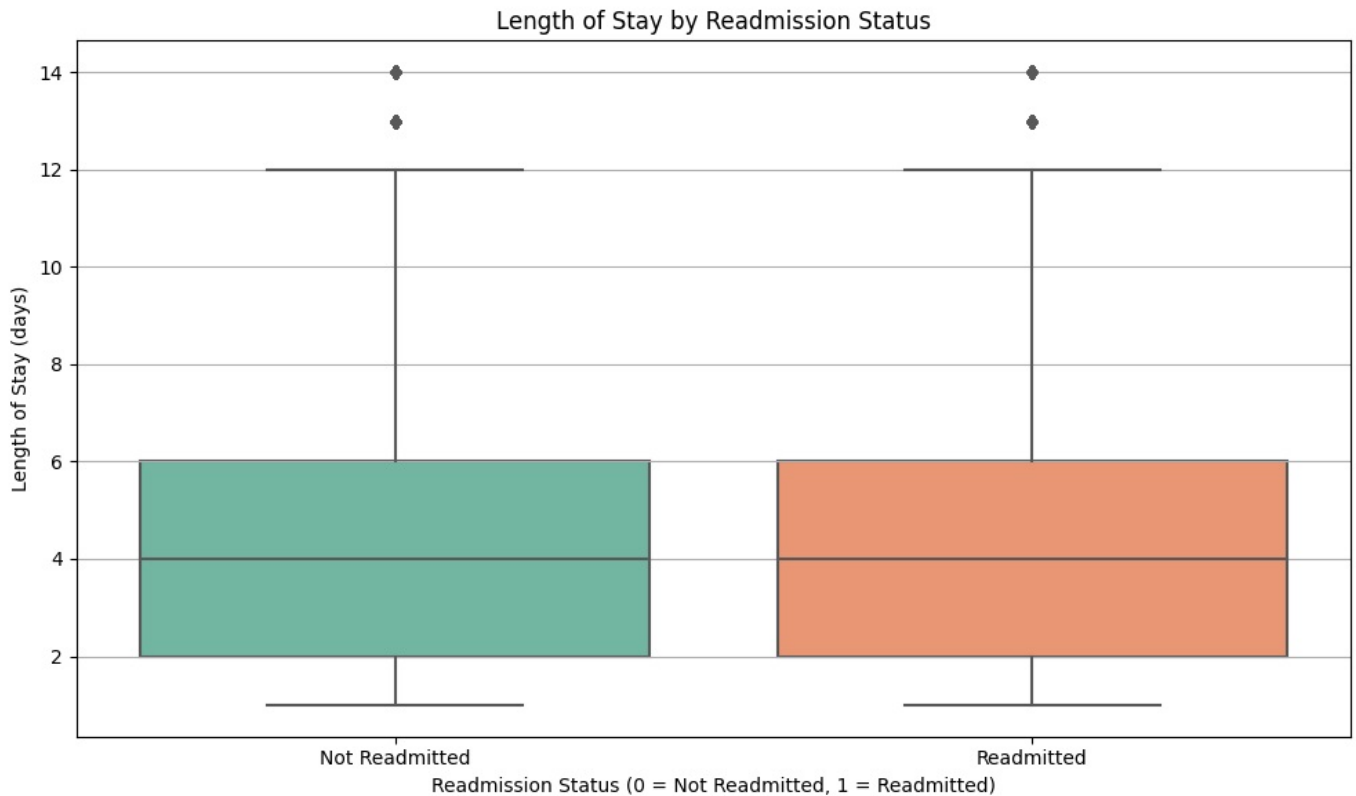
# Optional: Statistical test (t-test)
from scipy.stats import ttest_ind

# Split the data
readmitted = df[df['readmitted'] == 1]['time_in_hospital']
not_readmitted = df[df['readmitted'] == 0]['time_in_hospital']

# Perform t-test
t_stat, p_value = ttest_ind(readmitted, not_readmitted, equal_var=False)
print(f"T-test results: t-statistic = {t_stat:.2f}, p-value = {p_value:.4f}")
```

Summary Statistics for Length of Stay by Readmission Status:

	count	mean	std	min	25%	50%	75%	max
readmitted								
0	90409.0	4.349224	2.976382	1.0	2.0	4.0	6.0	14.0
1	11357.0	4.768249	3.028165	1.0	2.0	4.0	6.0	14.0



T-test results: t-statistic = 13.93, p-value = 0.0000

```
In [26]: import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, roc_auc_score, roc_curve
import matplotlib.pyplot as plt

# Step 1: Preprocessing
df['readmitted'] = df['readmitted'].replace({'<30': 1, '>30': 1, 'NO': 0}) # Encode readmitted as binary

# Feature and target variables
X = df[['time_in_hospital']] # Use length of stay as the predictor
y = df['readmitted']         # Readmission status as the target

# Step 2: Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)

# Step 3: Build and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Step 4: Evaluate the model
y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)[:, 1]

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```

# AUC-ROC score
roc_auc = roc_auc_score(y_test, y_pred_proba)
print(f"AUC-ROC Score: {roc_auc:.2f}")

# Plot the ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc:.2f})', color='blue')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid()
plt.show()

# Step 5: Interpretation
coef = model.coef_[0][0]
print(f"Logistic Regression Coefficient for time_in_hospital: {coef:.2f}")

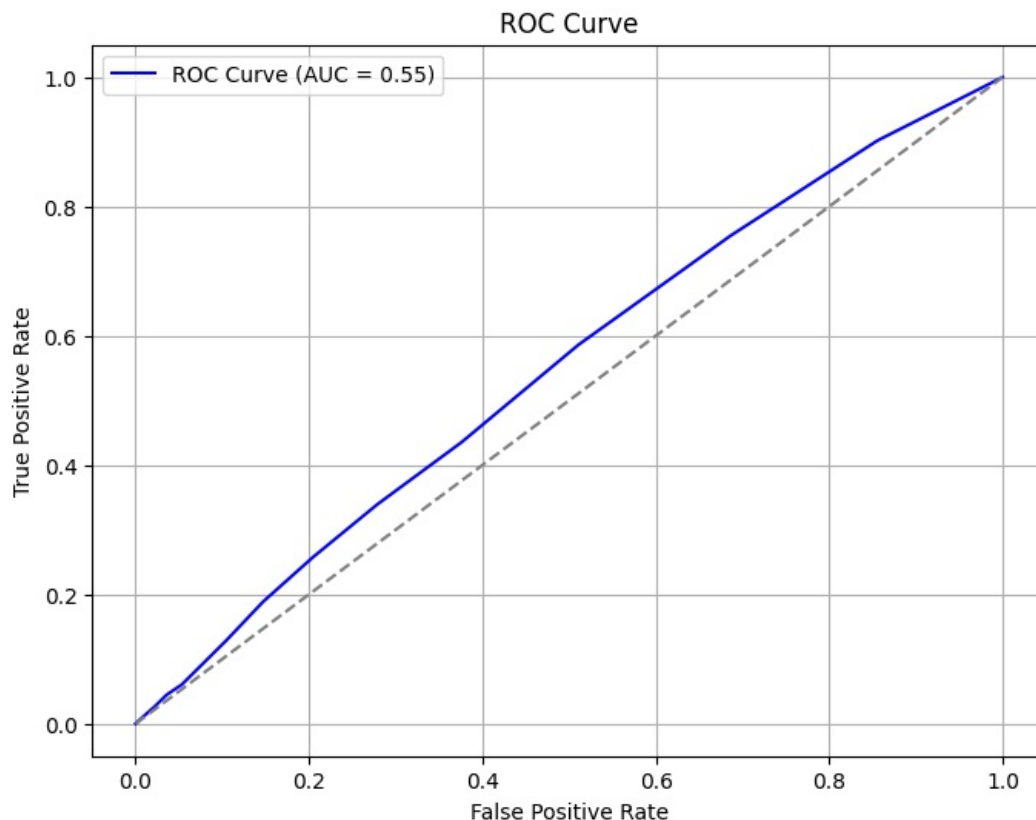
```

Classification Report:

	precision	recall	f1-score	support
0	0.89	1.00	0.94	27123
1	0.00	0.00	0.00	3407
accuracy			0.89	30530
macro avg	0.44	0.50	0.47	30530
weighted avg	0.79	0.89	0.84	30530

AUC-ROC Score: 0.55

C:\Users\nikde\AppData\Roaming\Python\Python311\site-packages\sklearn\metrics_classification.py:1471: Undefined MetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
warn_prf(average, modifier, msg_start, len(result))
C:\Users\nikde\AppData\Roaming\Python\Python311\site-packages\sklearn\metrics_classification.py:1471: Undefined MetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
warn_prf(average, modifier, msg_start, len(result))
C:\Users\nikde\AppData\Roaming\Python\Python311\site-packages\sklearn\metrics_classification.py:1471: Undefined MetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
warn_prf(average, modifier, msg_start, len(result))



Logistic Regression Coefficient for time_in_hospital: 0.04

In []:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js