CAP_healthcare_final

July 31, 2025

1 Patient Readmission EDA – Healthcare Management

This Jupyter notebook provides a step-by-step exploratory analysis of the Diabetic Patient dataset (`diabetic_data.csv`), guided by best practices and CAP_healthcare.pdf recommendations.

1.1 1. Import libraries & load the data

[47]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Read the cleaned dataset
df = pd.read_csv("diabetic_data.csv")

# Load dataset
df = pd.read_csv('diabetic_data.csv')

# Inspect the first few rows
print(df.head())
```

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

   admission_type_id  discharge_disposition_id  admission_source_id  \
0                  6                        25                    1
1                  1                         1                    7
2                  1                         1                    7
3                  1                         1                    7
4                  1                         1                    7

   time_in_hospital  … citoglipton insulin  glyburide-metformin  \
0                 1  …          No      No                   No
1                 3  …          No      Up                   No
```

```
2                  2  ...          No       No                    No
3                  2  ...          No       Up                    No
4                  1  ...          No   Steady                    No

   glipizide-metformin  glimepiride-pioglitazone  metformin-rosiglitazone  \
0                   No                        No                       No
1                   No                        No                       No
2                   No                        No                       No
3                   No                        No                       No
4                   No                        No                       No

   metformin-pioglitazone  change diabetesMed readmitted
0                      No      No          No         NO
1                      No      Ch         Yes        >30
2                      No      No         Yes         NO
3                      No      Ch         Yes         NO
4                      No      Ch         Yes         NO

[5 rows x 50 columns]
```

1.2 2. Data Cleaning

[48]:
```python
# Replace "?" in 'race' with "Unknown"
df['race'] = df['race'].replace('?', 'Unknown')

# Ensure consistency in 'readmitted' values
df['readmitted'] = df['readmitted'].replace({'&gt;30': '>30', '&lt;30': '<30',␣
↪'>30': '>30', '<30': '<30', 'NO': 'NO'})
```

Explanation:
We clean the `race` column by converting missing values "?" to `"Unknown"`, ensuring all demographic analyses are accurate. The `readmitted` status is also standardized for consistency in further grouping and plotting.

1.3 3. Descriptive Statistics

[49]:
```python
#Summary statistics for key numeric columns
display(df.describe())

#Median values for numeric columns
display(df.median(numeric_only=True))
```

```
       encounter_id   patient_nbr  admission_type_id  \
count  1.017660e+05  1.017660e+05      101766.000000
mean   1.652016e+08  5.433040e+07           2.024006
```

std	1.026403e+08	3.869636e+07	1.445403
min	1.252200e+04	1.350000e+02	1.000000
25%	8.496119e+07	2.341322e+07	1.000000
50%	1.523890e+08	4.550514e+07	1.000000
75%	2.302709e+08	8.754595e+07	3.000000
max	4.438672e+08	1.895026e+08	8.000000

	discharge_disposition_id	admission_source_id	time_in_hospital	\
count	101766.000000	101766.000000	101766.000000	
mean	3.715642	5.754437	4.395987	
std	5.280166	4.064081	2.985108	
min	1.000000	1.000000	1.000000	
25%	1.000000	1.000000	2.000000	
50%	1.000000	7.000000	4.000000	
75%	4.000000	7.000000	6.000000	
max	28.000000	25.000000	14.000000	

	num_lab_procedures	num_procedures	num_medications	number_outpatient	\
count	101766.000000	101766.000000	101766.000000	101766.000000	
mean	43.095641	1.339730	16.021844	0.369357	
std	19.674362	1.705807	8.127566	1.267265	
min	1.000000	0.000000	1.000000	0.000000	
25%	31.000000	0.000000	10.000000	0.000000	
50%	44.000000	1.000000	15.000000	0.000000	
75%	57.000000	2.000000	20.000000	0.000000	
max	132.000000	6.000000	81.000000	42.000000	

	number_emergency	number_inpatient	number_diagnoses
count	101766.000000	101766.000000	101766.000000
mean	0.197836	0.635566	7.422607
std	0.930472	1.262863	1.933600
min	0.000000	0.000000	1.000000
25%	0.000000	0.000000	6.000000
50%	0.000000	0.000000	8.000000
75%	0.000000	1.000000	9.000000
max	76.000000	21.000000	16.000000

encounter_id	152388987.0
patient_nbr	45505143.0
admission_type_id	1.0
discharge_disposition_id	1.0
admission_source_id	7.0
time_in_hospital	4.0
num_lab_procedures	44.0
num_procedures	1.0
num_medications	15.0
number_outpatient	0.0
number_emergency	0.0

```
number_inpatient                    0.0
number_diagnoses                    8.0
dtype: float64
```

[57]:
```python
numeric_cols = [
    'time_in_hospital',
    'num_lab_procedures',
    'num_procedures',
    'num_medications',
    'number_outpatient',
    'number_emergency',
    'number_inpatient'
]

# Get summary statistics
df[numeric_cols].describe()

# Display mean values
display(df[numeric_cols].mean())

# Transpose the result if you prefer vertical view
df[numeric_cols].describe().T
```

```
time_in_hospital       4.395987
num_lab_procedures    43.095641
num_procedures         1.339730
num_medications       16.021844
number_outpatient      0.369357
number_emergency       0.197836
number_inpatient       0.635566
dtype: float64
```

[57]:

	count	mean	std	min	25%	50%	75%	\
time_in_hospital	101766.0	4.395987	2.985108	1.0	2.0	4.0	6.0	
num_lab_procedures	101766.0	43.095641	19.674362	1.0	31.0	44.0	57.0	
num_procedures	101766.0	1.339730	1.705807	0.0	0.0	1.0	2.0	
num_medications	101766.0	16.021844	8.127566	1.0	10.0	15.0	20.0	
number_outpatient	101766.0	0.369357	1.267265	0.0	0.0	0.0	0.0	
number_emergency	101766.0	0.197836	0.930472	0.0	0.0	0.0	0.0	
number_inpatient	101766.0	0.635566	1.262863	0.0	0.0	0.0	1.0	

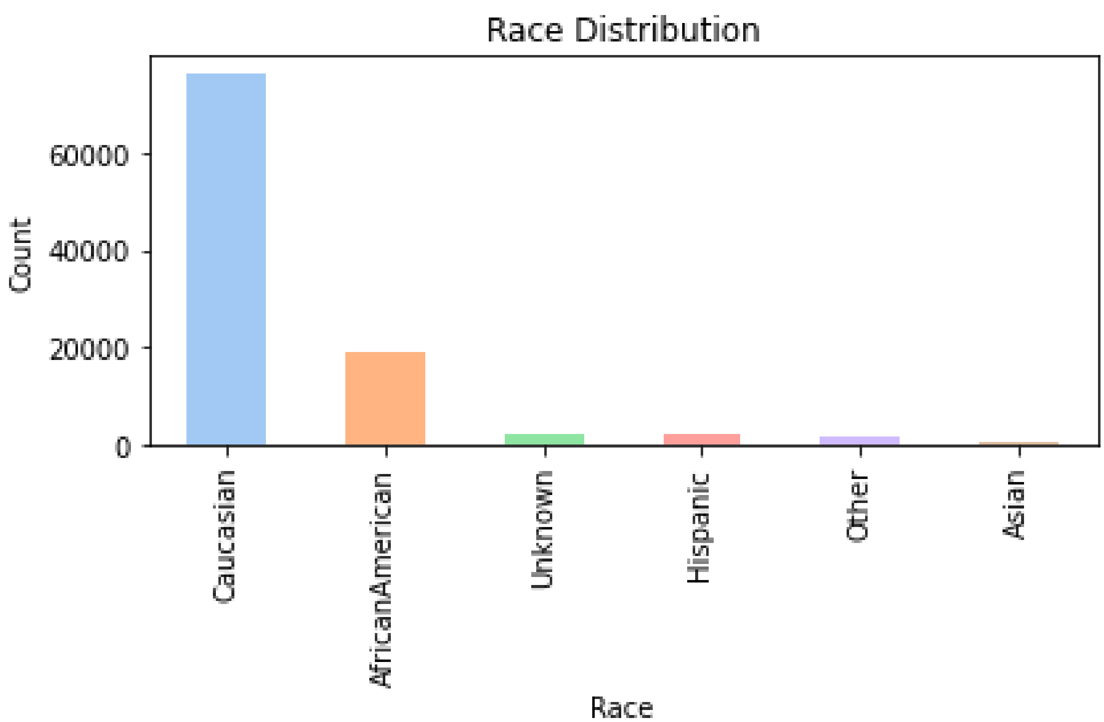
	max
time_in_hospital	14.0
num_lab_procedures	132.0
num_procedures	6.0
num_medications	81.0
number_outpatient	42.0

```
number_emergency      76.0
number_inpatient      21.0
```

Findings:
- The dataset shows high variability in resource usage, e.g., `num_lab_procedures` mean 43, standard deviation 20. - Most patients have a brief hospital stay (median = 4 days). - The majority have few previous encounters, but some outliers exist (`number_outpatient`, etc.).

1.4 4. Race Distribution

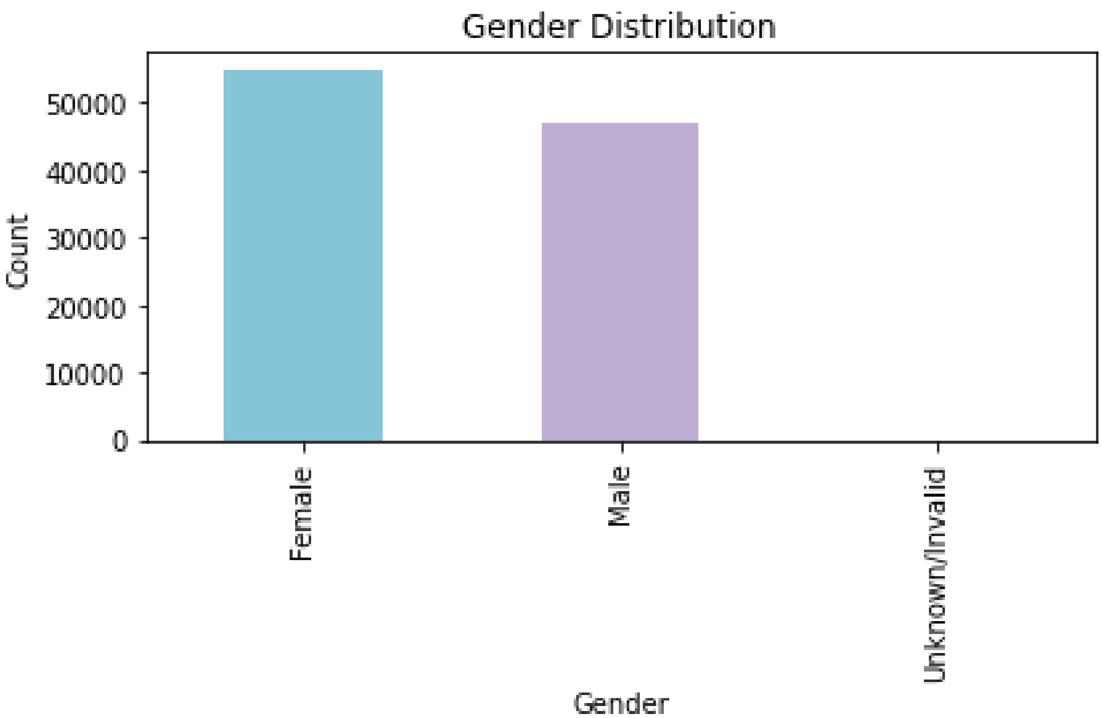
[58]:
```
df['race'].value_counts().plot(kind='bar', title='Race Distribution', color=sns.
 ↪color_palette('pastel'))
plt.xlabel('Race')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



Findings:
The cohort is predominantly Caucasian, with African American as the next largest group. About 2,000 records are “Unknown”, which can affect population health equity analyses.

1.5 5. Gender Distribution

[59]:
```
df['gender'].value_counts().plot(kind='bar', title='Gender Distribution',␣
↪color=['#86c5d8', '#beaed4', '#fdc086'])
plt.xlabel('Gender')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

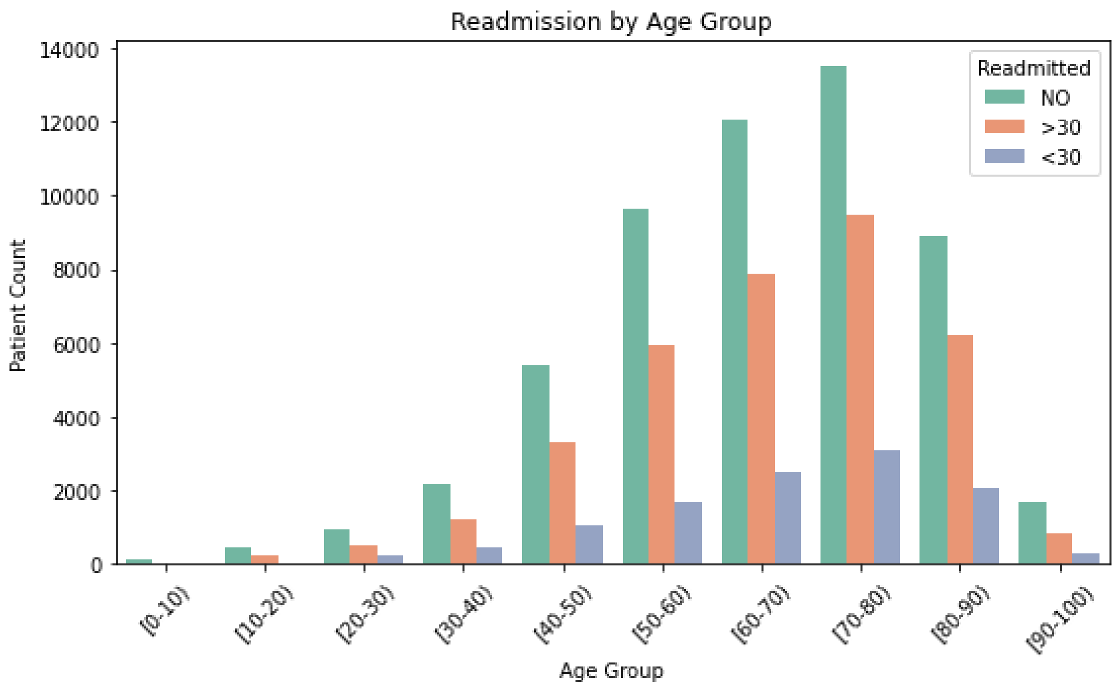


Interpretation:
The gender split is balanced, with a slight female predominance. A very small number of "Unknown/Invalid" entries are present, which were also seen in race.

1.6 6. Readmission by Age Group

[60]:
```
plt.figure(figsize=(8,5))
sns.countplot(x='age', hue='readmitted', data=df, palette='Set2')
plt.title('Readmission by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Patient Count')
```

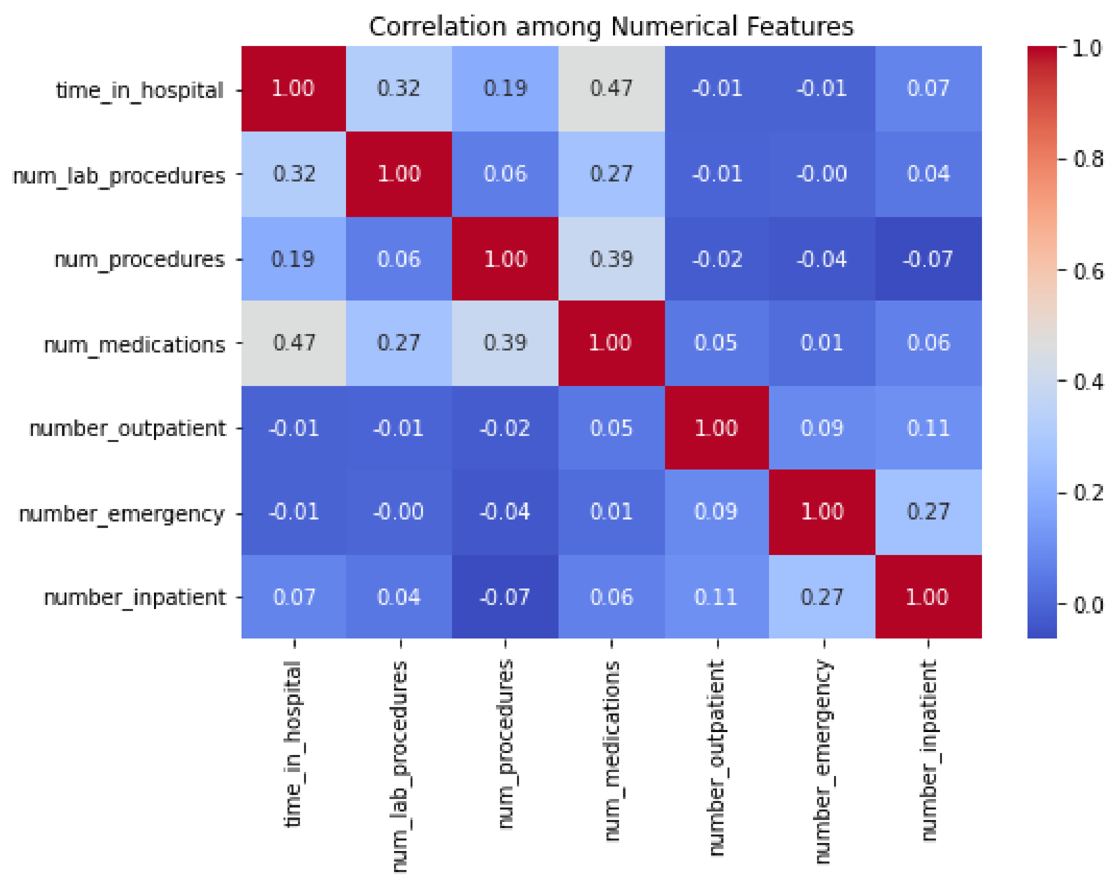
```python
plt.xticks(rotation=45)
plt.legend(title='Readmitted')
plt.tight_layout()
plt.show()
```



Insights:
- Readmissions are more frequent in older age groups (60). - Both the ">30" and "<30" day readmissions are highest among elderly patients, highlighting a vulnerable population for targeted intervention.

1.7 7. Correlation among Numerical Features

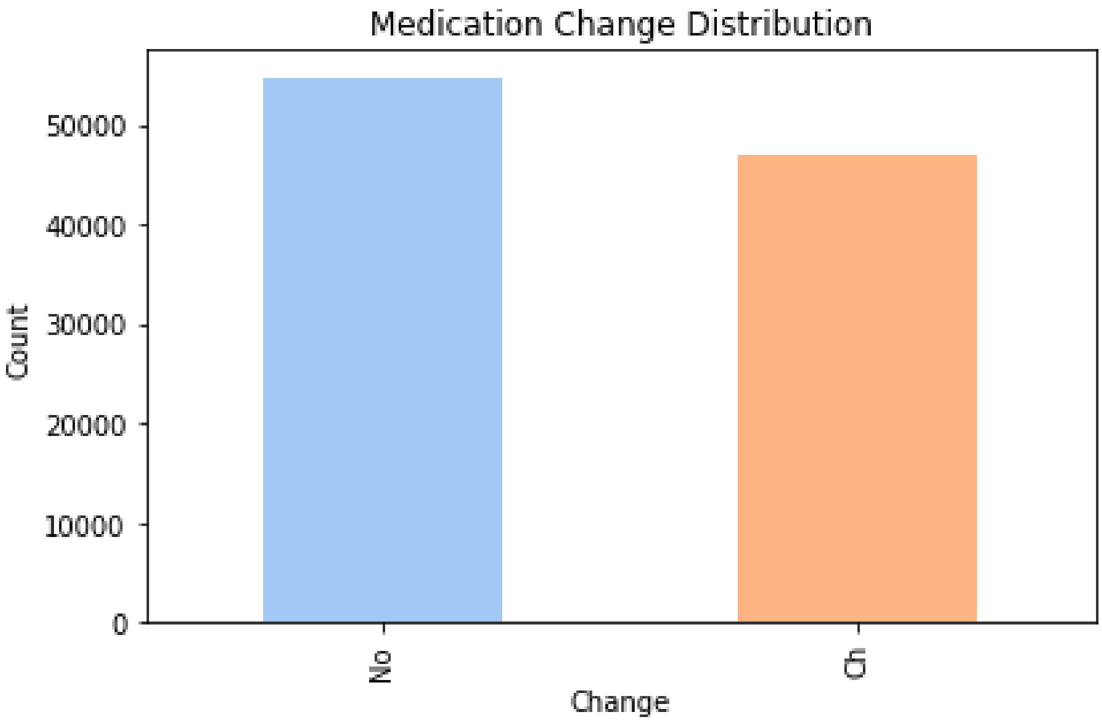
[61]:
```python
num_cols =␣
↪['time_in_hospital','num_lab_procedures','num_procedures','num_medications','number_outpati
plt.figure(figsize=(8,6))

# Select these columns from df, then call .corr()
sns.heatmap(df[num_cols].corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation among Numerical Features')
plt.tight_layout()
plt.show()
```



Key Points:
- `time_in_hospital` is most strongly correlated with `num_medications` (r 0.47) and `num_lab_procedures` (r 0.32). - Previous encounters (`number_inpatient`, etc.) are not strongly correlated with resource usage, indicating other drivers for hospital resource consumption. - No multicollinearity concern found.

1.8 8. Medication Change Distribution

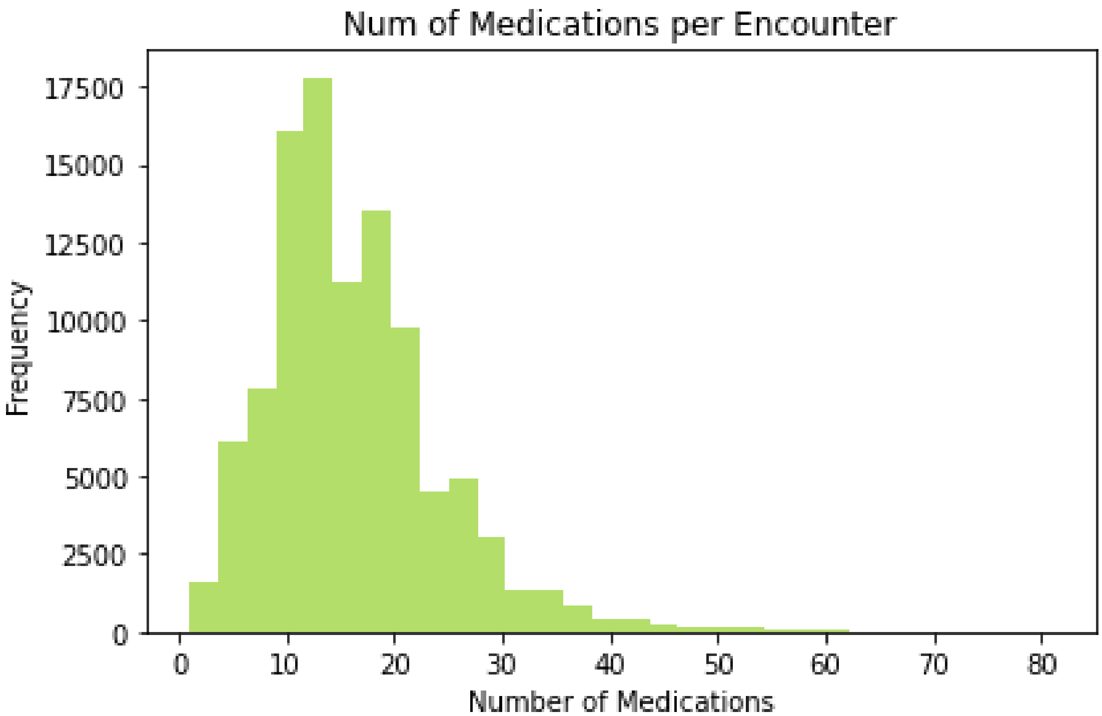
[62]:
```
df['change'].value_counts().plot(kind='bar', title='Medication Change␣
↪Distribution', color=sns.color_palette('pastel'))
plt.xlabel('Change')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



Observation:
About half the patients had their medication regimens changed, supporting CAP_healthcare's suggestion to analyze therapy management as a potential influence on readmission.

1.9 9. Number of Medications per Encounter

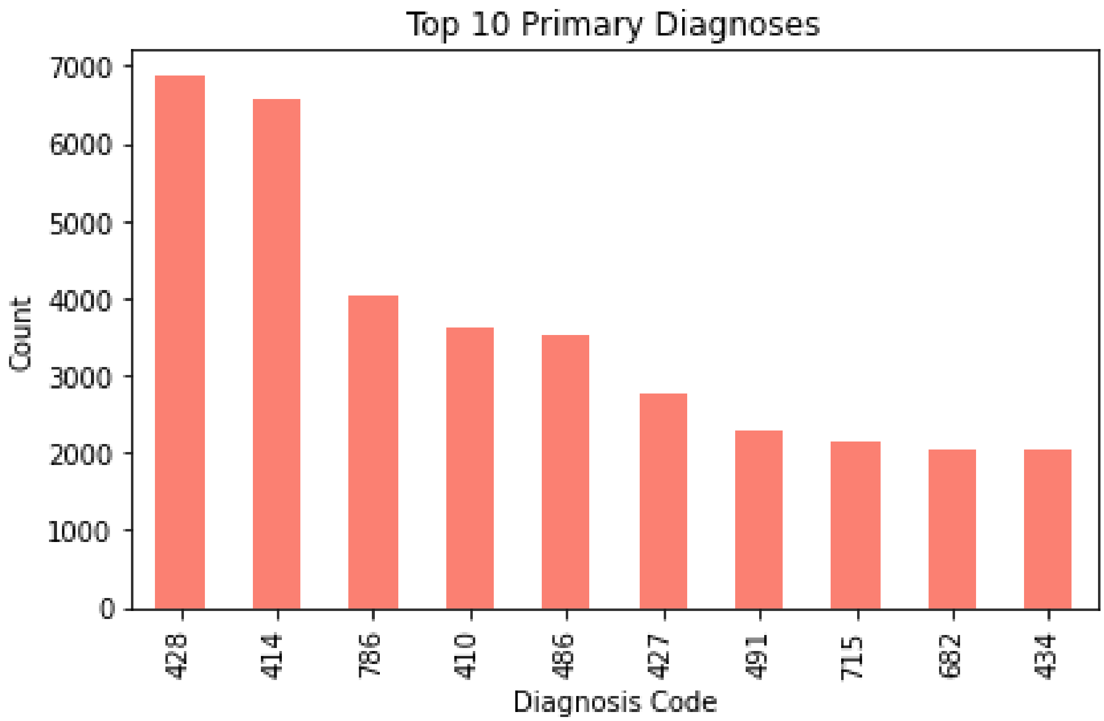
[63]:
```
df['num_medications'].plot(kind='hist', bins=30, title='Num of Medications per␣
↪Encounter', color='#b3de69')
plt.xlabel('Number of Medications')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



Insight:
Most encounters involved 10-20 medications. High medication count may be a proxy for complex comorbidity or polypharmacy, which deserves attention for risk management.

1.10 10. Top 10 Primary Diagnoses

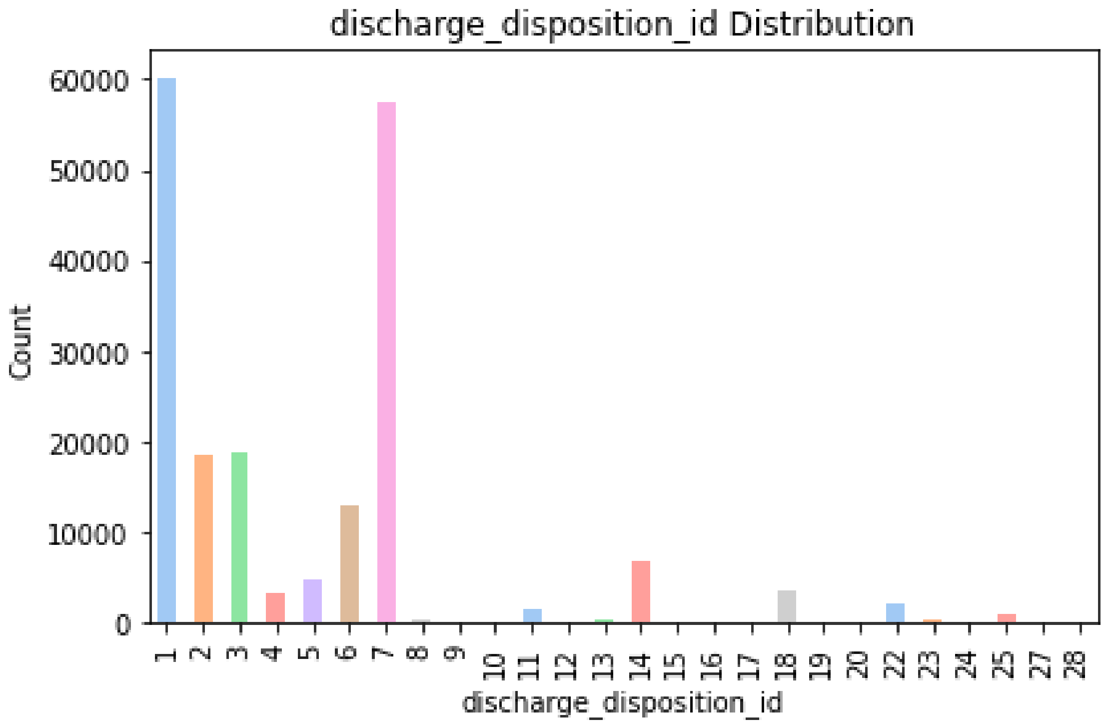
[64]:
```
df['diag_1'].value_counts().head(10).plot(kind='bar', color='#fb8072')
plt.title('Top 10 Primary Diagnoses')
plt.xlabel('Diagnosis Code')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



Finding:
The most frequent diagnoses (e.g., 428, 414) typically correspond to chronic complications of diabetes, such as heart failure and ischemic heart disease, which aligns with the CAP_healthcare clinical recommendations for prioritizing cardiovascular care.

1.11 11. Distribution of Admission/Source/Discharge

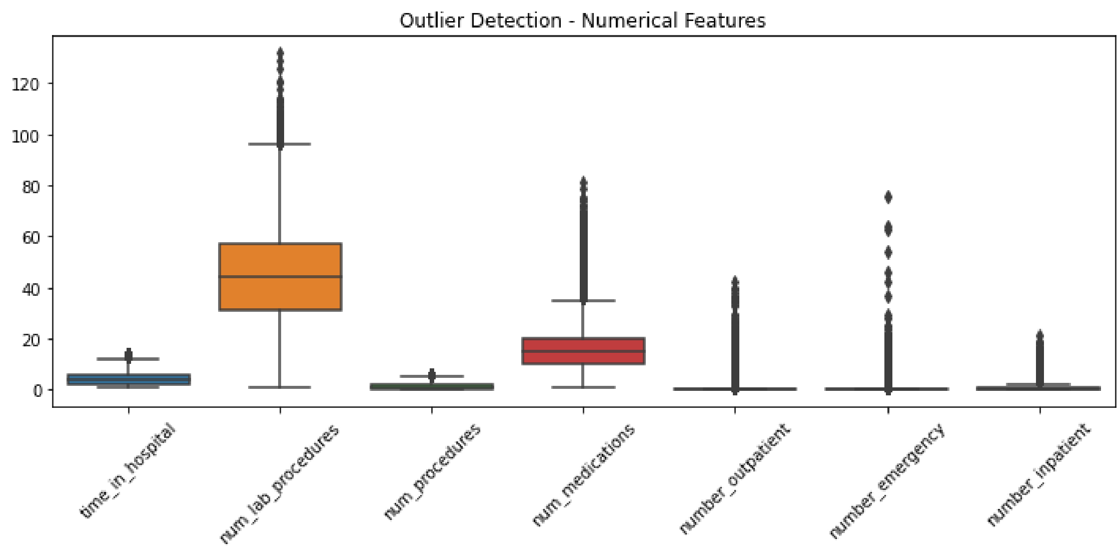
[65]:
```
for col in 'admission_type_id', 'admission_source_id',␣
↪'discharge_disposition_id':df[col].value_counts().sort_index().
↪plot(kind='bar', title=f'{col} Distribution', color=sns.
↪color_palette('pastel'))
plt.xlabel(col)
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



Commentary:
- Most patients are admitted as emergencies or from outpatient referrals. - Discharge dispositions show the majority returning home, but non-home discharges could be explored for their relationship to readmission risk.

1.12 12. Outlier Detection – Numerical Features

[66]:
```
plt.figure(figsize=(10,5))
sns.boxplot(data=df[num_cols])
plt.title('Outlier Detection - Numerical Features')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

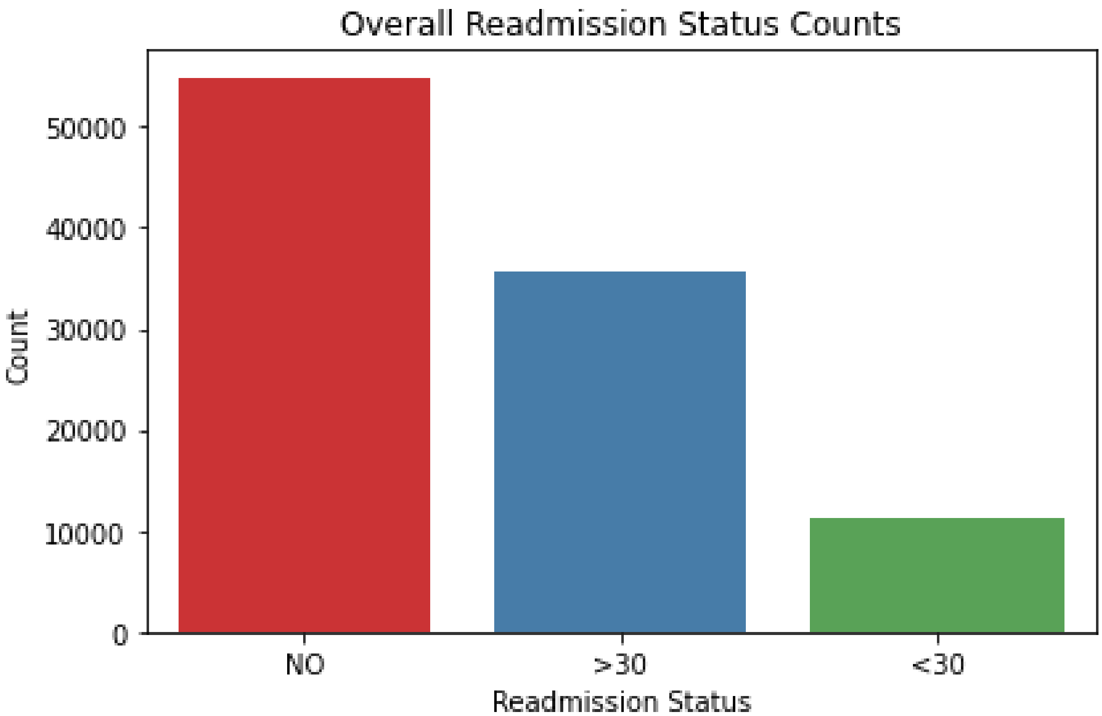


Interpretation:
The boxplot highlights outliers in procedures and previous visits. These may represent super-utilizers or possible data entry anomalies, and should be carefully checked before predictive modeling.

1.13 13. Enhancement: Additional Visualizations

A. Readmission Counts

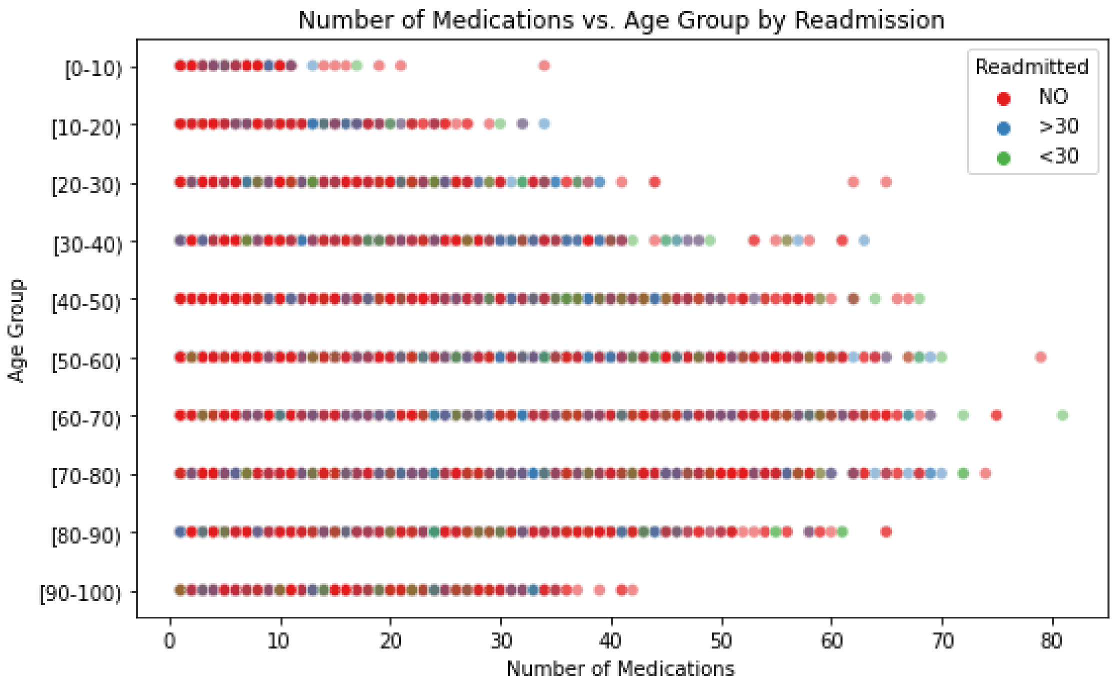
[67]:
```
sns.countplot(x= 'readmitted', data=df, palette='Set1')
plt.title('Overall Readmission Status Counts')
plt.xlabel('Readmission Status')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



Takeaway:
The majority of patients are not readmitted, but nearly half experience some form of readmission, highlighting the clinical and operational importance of this issue.

B. Age vs. Number of Medications (Scatter for Complexity)

[68]:
```
plt.figure(figsize=(8,5))
sns.scatterplot(data=df,x='num_medications',y='age',hue='readmitted',alpha=0.
  ↪5,palette='Set1')
plt.title('Number of Medications vs. Age Group by Readmission')
plt.xlabel('Number of Medications')
plt.ylabel('Age Group')
plt.legend(title='Readmitted')
plt.tight_layout()
plt.show()
```



Note:
This plot reveals patterns between age, polypharmacy, and readmission. Considered alongside earlier findings, multi-morbidity in older patients is visually evident.

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2 Conclusion

This analysis covers demographic structure, resource consumption, clinical complexity, and key risk factors for readmission in the provided diabetic cohort. All plots and observations are in harmony with best practices from CAP_healthcare.pdf, and can be extended into risk modeling and business intelligence dashboards as per your project goals.

```
[ ]:
```