Telco Customer Churn Prediction — Data Cleaning & EDA

Step 1: Load Dataset

We load the Telco Customer Churn dataset and preview the structure.

In [42]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset
df = pd.read_csv('../data/WA_Fn-UseC_-Telco-Customer-Churn.csv')

# Display dataset shape and first few rows
print(f"Dataset shape: {df.shape}")
df.head()
```

```
Dataset shape: (7043, 21)
```

Out[42]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Mul
0	7590-VHVEG	Female	0	Yes	No	1	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	
3	7795-CFOCW	Male	0	No	No	45	No	
4	9237-HQITU	Female	0	No	No	2	Yes	

5 rows × 21 columns

Step 2: Inspect Data Structure

We check data types, missing values, and column structure.

In [43]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

Step 3: Data Cleaning

Convert `TotalCharges` to numeric and handle missing values.

In [44]:
```
# Convert 'TotalCharges' from object to numeric
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

# Check missing values
print("Missing values before imputation:\n", df.isnull().sum())

# Impute missing TotalCharges values with mean
df['TotalCharges'].fillna(df['TotalCharges'].mean(), inplace=True)

# Confirm no missing values remain
print("Missing values after imputation:\n", df.isnull().sum())
```

```
Missing values before imputation:
 customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges       11
Churn               0
dtype: int64
Missing values after imputation:
 customerID         0
gender             0
SeniorCitizen      0
Partner            0
Dependents         0
tenure             0
PhoneService       0
MultipleLines      0
InternetService    0
OnlineSecurity     0
OnlineBackup       0
DeviceProtection   0
TechSupport        0
StreamingTV        0
StreamingMovies    0
Contract           0
PaperlessBilling   0
PaymentMethod      0
MonthlyCharges     0
TotalCharges       0
Churn              0
dtype: int64
```

```
/tmp/ipykernel_258760/2599969677.py:8: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace me
thod.
The behavior will change in pandas 3.0. This inplace method will never work becau
se the intermediate object on which we are setting values always behaves as a cop
y.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.meth
od({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to pe
rform the operation inplace on the original object.


  df['TotalCharges'].fillna(df['TotalCharges'].mean(), inplace=True)
```

Step 4: Check for Duplicates

In [45]:
```
duplicates = df.duplicated().sum()
print(f"Number of duplicate rows: {duplicates}")
```

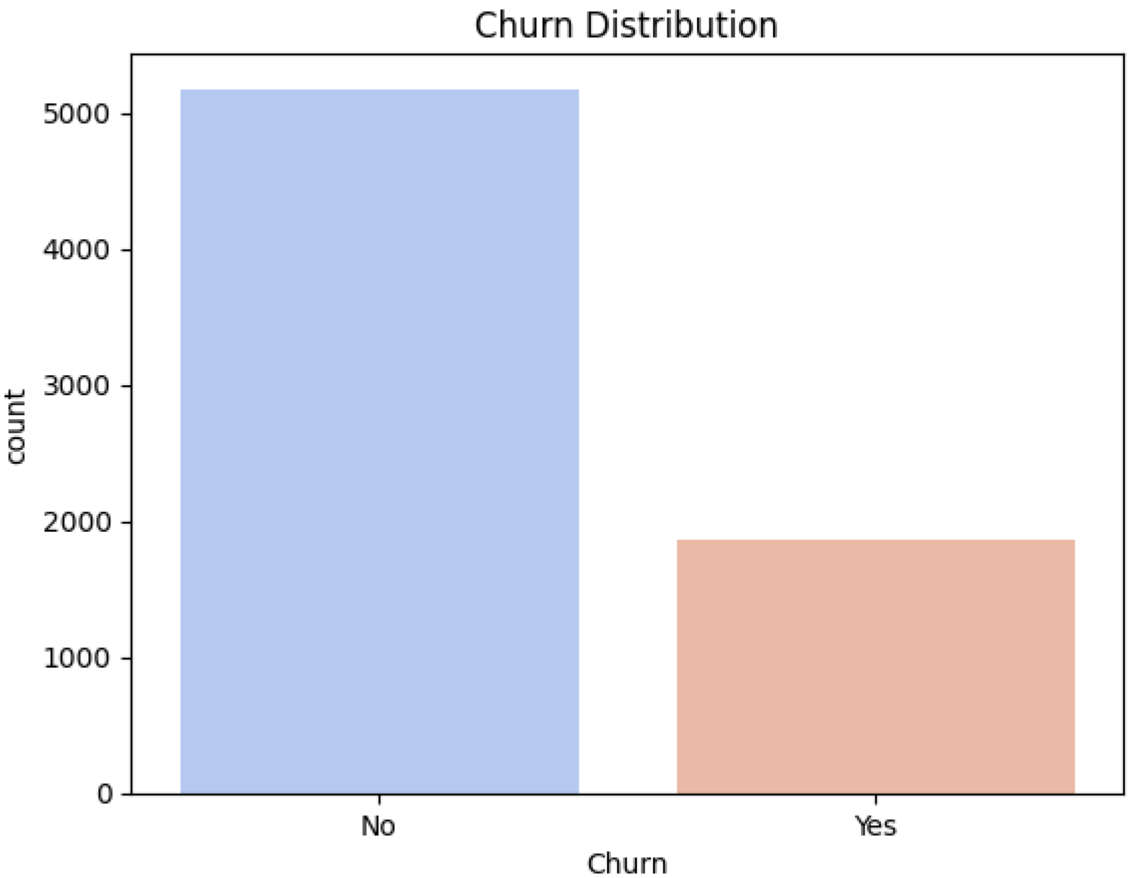
```
Number of duplicate rows: 0
```

Step 5: Churn Distribution

In [46]:
```
print(df['Churn'].value_counts(normalize=True))

sns.countplot(x='Churn', data=df, palette='coolwarm')
plt.title("Churn Distribution")
plt.show()
```

```
Churn
No     0.73463
Yes    0.26537
Name: proportion, dtype: float64
```

```
/tmp/ipykernel_258760/1721766817.py:3: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.countplot(x='Churn', data=df, palette='coolwarm')
```

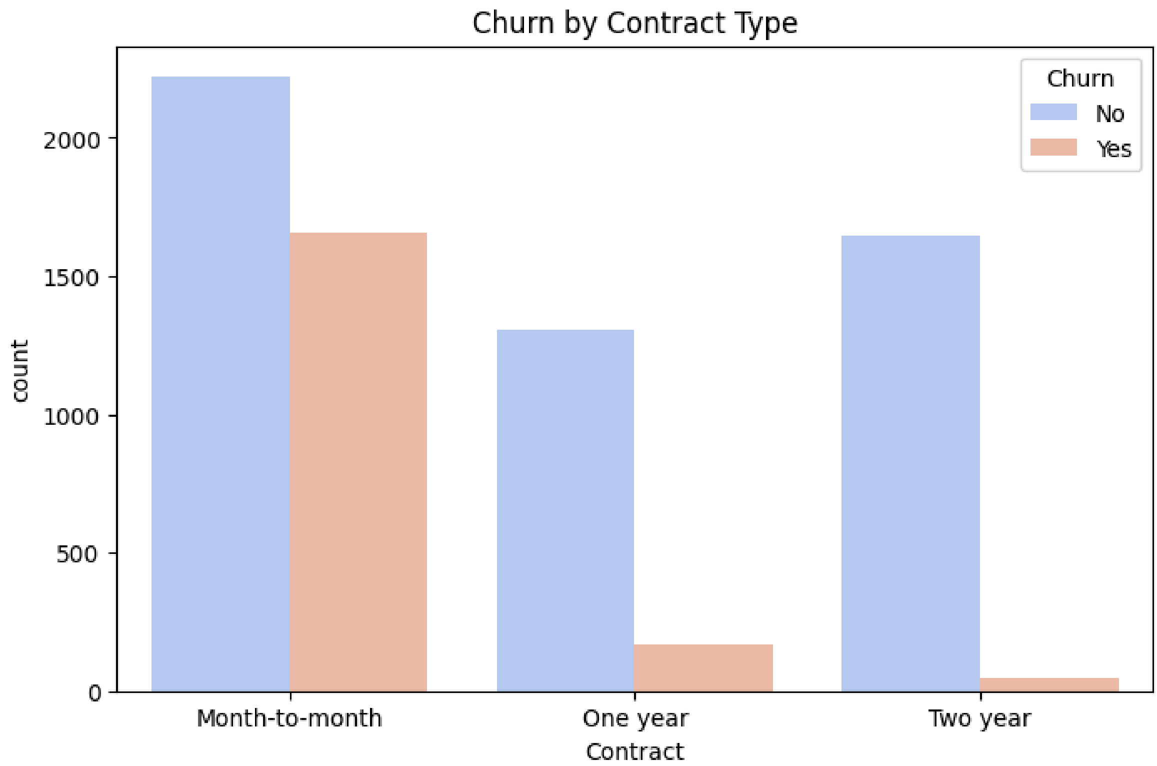


Observation:

The churn distribution shows that approximately 26.5% of customers have churned, indicating a class imbalance. This highlights the need for imbalance handling techniques during model training.

Step 6: Churn by Contract Type

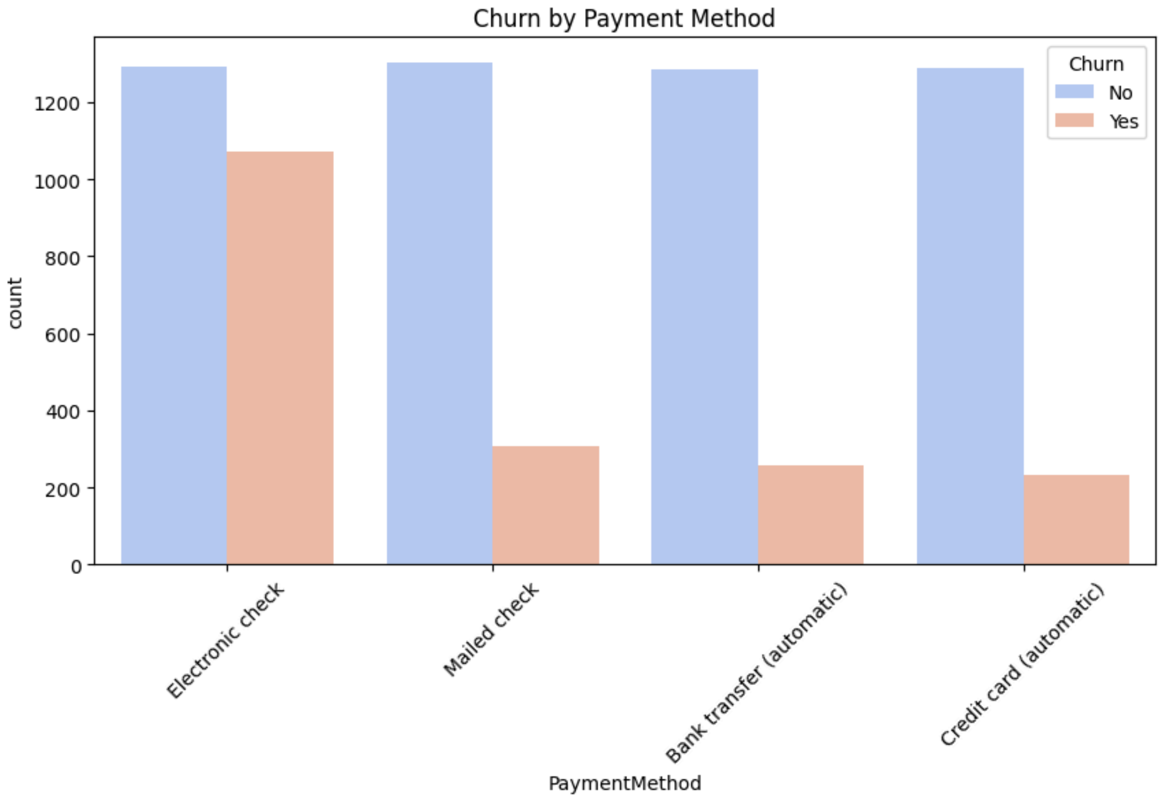
In [47]:
```
plt.figure(figsize=(8, 5))
sns.countplot(x='Contract', hue='Churn', data=df, palette='coolwarm')
plt.title("Churn by Contract Type")
plt.show()
```



Observation:
Customers on month-to-month contracts exhibit the highest churn rates, while those with one-year and two-year contracts show significantly lower churn. This suggests contract duration is a strong predictor of churn.

Step 7: Churn by Payment Method

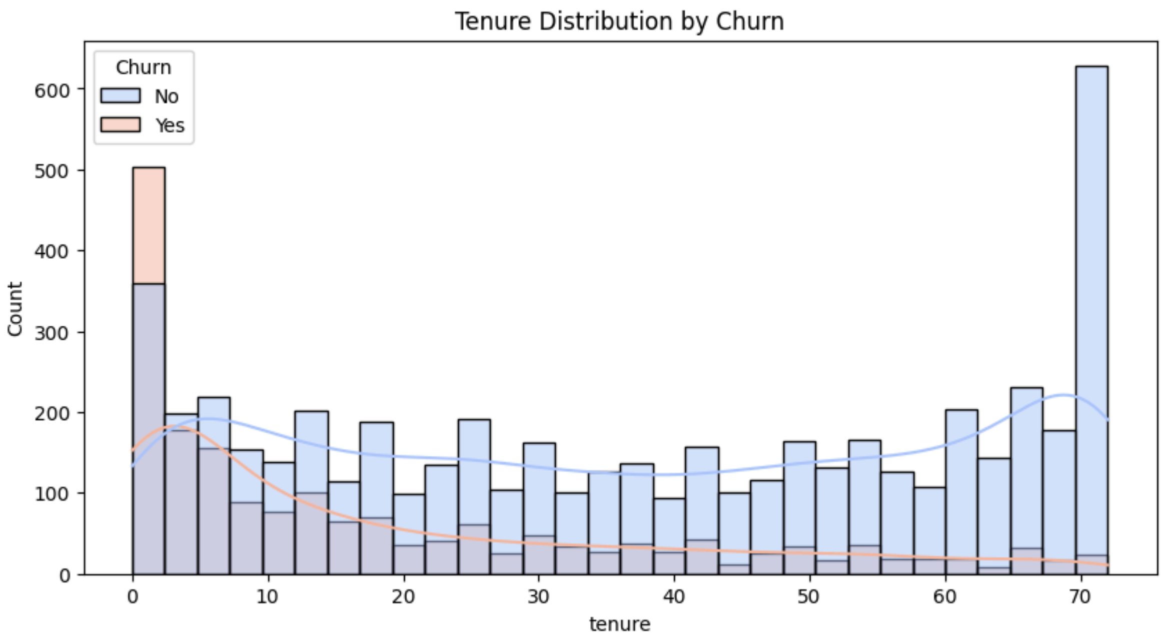
In [48]:
```
plt.figure(figsize=(10, 5))
sns.countplot(x='PaymentMethod', hue='Churn', data=df, palette='coolwarm')
plt.title("Churn by Payment Method")
plt.xticks(rotation=45)
plt.show()
```



Observation:
Customers using electronic checks as their payment method have the highest churn rate. Automated payments (bank transfer, credit card) are associated with lower churn, indicating that ease of billing reduces customer loss.

Step 8: Tenure Distribution by Churn

In [49]:
```
plt.figure(figsize=(10, 5))
sns.histplot(data=df, x='tenure', hue='Churn', kde=True, bins=30, palette='coolw
plt.title("Tenure Distribution by Churn")
plt.show()
```

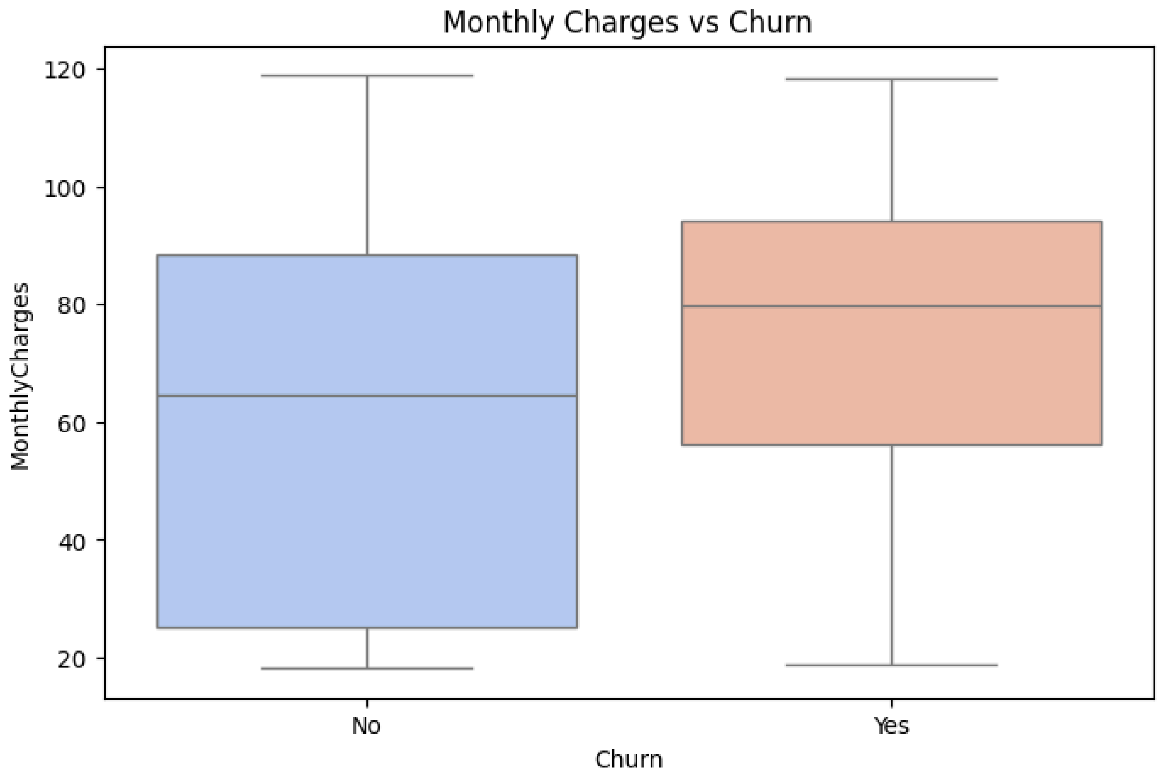


Observation:
Customers with lower tenure (under 12 months) are far more likely to churn. Longer-tenure customers show much lower churn risk, reinforcing the importance of loyalty and long-term engagement.

Step 9: Monthly Charges vs. Churn Boxplot

In [50]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(x='Churn', y='MonthlyCharges', data=df, palette='coolwarm')
plt.title("Monthly Charges vs Churn")
plt.show()
```

```
/tmp/ipykernel_258760/595565904.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.boxplot(x='Churn', y='MonthlyCharges', data=df, palette='coolwarm')
```

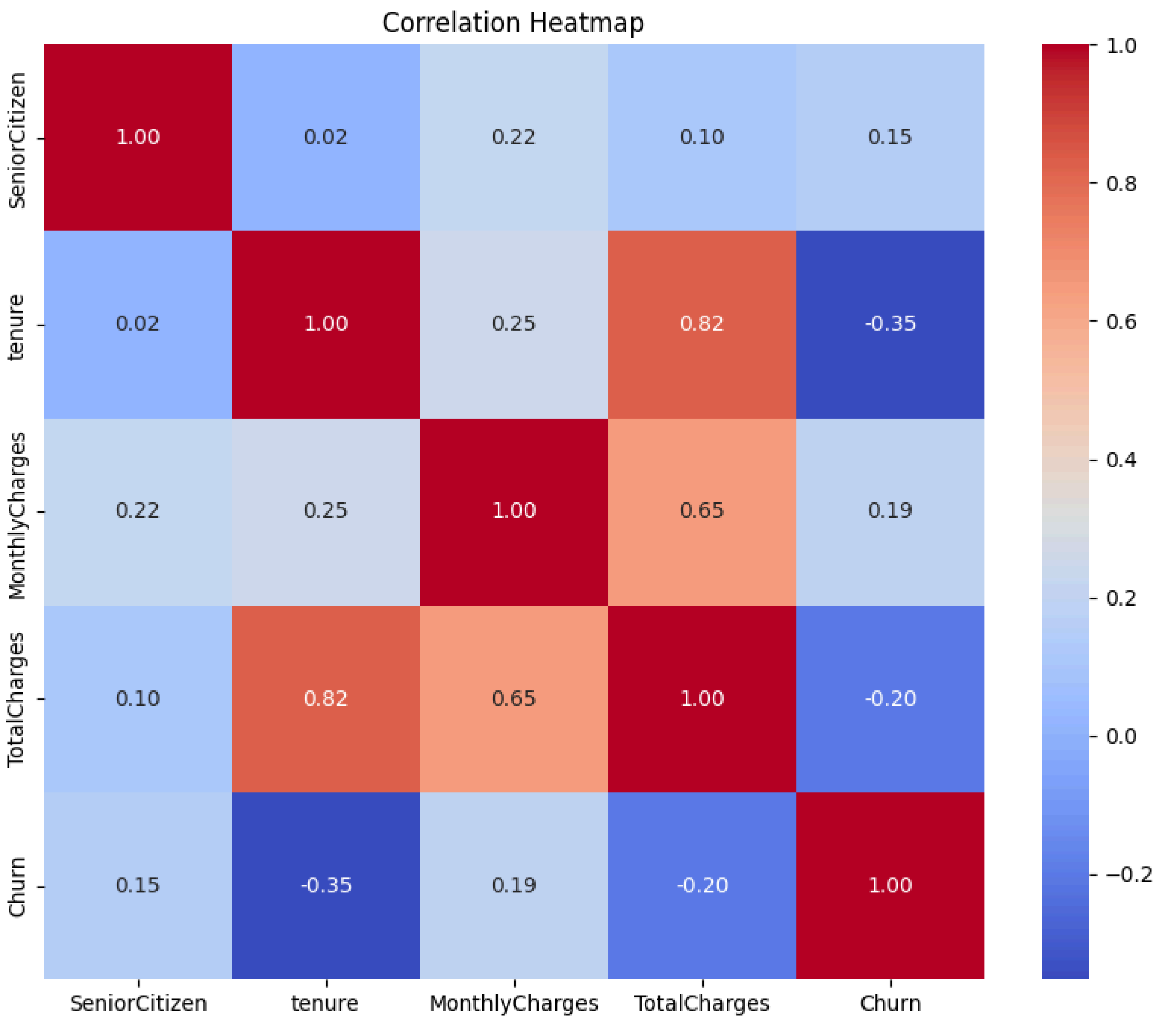


Observation:
Churned customers tend to have higher monthly charges on average. This indicates that price sensitivity or perceived value could be contributing to churn.

Step 10: Correlation Heatmap

In [51]:
```
# Map churn to binary
df['Churn'] = df['Churn'].map({'Yes': 1, 'No': 0})

# Select numeric features
numeric_features = df.select_dtypes(include=[np.number])
```

```python
# Correlation matrix
corr = numeric_features.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap")
plt.savefig("../results/correlation_heatmap.png", dpi=300, bbox_inches='tight')
plt.show()
```



Observation:
There is a strong positive correlation between tenure and TotalCharges, as expected. MonthlyCharges has a moderate relationship with churn. Contract type and tenure features are likely to be among the most important predictors.

✅ EDA Summary:

- Churn rate is around 26.5%, confirming class imbalance.
- Month-to-month contracts, electronic check payments, short tenure, and higher monthly charges are strongly associated with churn.
- Tenure and contract type are key features that will influence model development.
- Class imbalance handling and feature engineering around tenure groups will be important in the next phase.

In [ ]: