Churn Prediction and Business Insight with Data Science at MTN Nigeria

This project was built using the “MTN Nigeria Customer Churn” dataset taken from Kaggle (https://www.kaggle.com/datasets/oluwademiladeadeniyi/mtn-nigeria-customer-churn/). MTN Nigeria is one of the largest telecommunications service providers in Nigeria and the main branch of the MTN group, with millions of customers across the country.

With this workflow, I hope to generate actionable insights to help MTN Nigeria reduce churn and improve customer retention.

> **Disclaimer:** ***The analysis and insights in this project were prepared as part of a personal data analysis and business skills development exercise. The data used is from open sources. Each insight aims to exercise an analytical mindset and is not intended as a professional business recommendation.***

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import StratifiedKFold
from sklearn.feature_selection import RFECV
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
import warnings
```

In [2]:
```
data = pd.read_csv('Dataset/mtn_customer_churn.csv')

df = data.copy()
```

Problem Understanding

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

Out[3]:

	Customer ID	Full Name	Date of Purchase	Age	State	MTN Device	Gender	Satisfaction Rate	Custom Revie
0	CUST0001	Ngozi Berry	Jan-25	27	Kwara	4G Router	Male	2	Fa
1	CUST0002	Zainab Baker	Mar-25	16	Abuja (FCT)	Mobile SIM Card	Female	2	Fa
2	CUST0003	Saidu Evans	Mar-25	21	Sokoto	5G Broadband Router	Male	1	Po
3	CUST0003	Saidu Evans	Mar-25	21	Sokoto	Mobile SIM Card	Male	1	Po
4	CUST0003	Saidu Evans	Mar-25	21	Sokoto	Broadband MiFi	Male	1	Po

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 974 entries, 0 to 973
Data columns (total 17 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Customer ID                  974 non-null    object 
 1   Full Name                    974 non-null    object 
 2   Date of Purchase             974 non-null    object 
 3   Age                          974 non-null    int64  
 4   State                        974 non-null    object 
 5   MTN Device                   974 non-null    object 
 6   Gender                       974 non-null    object 
 7   Satisfaction Rate            974 non-null    int64  
 8   Customer Review              974 non-null    object 
 9   Customer Tenure in months    974 non-null    int64  
 10  Subscription Plan            974 non-null    object 
 11  Unit Price                   974 non-null    int64  
 12  Number of Times Purchased    974 non-null    int64  
 13  Total Revenue                974 non-null    int64  
 14  Data Usage                   974 non-null    float64
 15  Customer Churn Status        974 non-null    object 
 16  Reasons for Churn            284 non-null    object 
dtypes: float64(1), int64(6), object(10)
memory usage: 129.5+ KB
```

In [5]:
```
df['Customer Churn Status'].value_counts()
```

Out[5]:
```
Customer Churn Status
No     690
Yes    284
Name: count, dtype: int64
```

In [6]:
```
persentage_churn = (round((len(df[df['Customer Churn Status'] == 'Yes']) / len(d
```

```
print(f'Percentage of customers who churned: {persentage_churn}%')
```

```
Percentage of customers who churned: 29.16%
```

Customer churn is one of the biggest concerns for telecom companies, especially in competitive markets like Nigeria.

This issue requires serious attention. We need to address it effectively or at least reduce the churn rate. But how? First, we must gain a deeper understanding of two critical metrics:

1. Customer Satisfaction Score (CSAT)
2. Monthly Recurring Revenue

These metrics are key to identifying the underlying issues. To do this, we should begin by visualizing the data to uncover trends and patterns. Understanding why customers are more likely to churn is essential. Currently, the churn rate stands at 29%, which is significantly high for telecom companies in Nigeria.

For context, the average churn rate for telecom companies in the United States is around 21%, according to ExplodingTopics.com.

Data Preparation

We need to first understand the data and identify what insights can be extracted from it.

In [7]:
```
# Check for missing values
missing_values = df.isnull().sum()
print("Missing values in each column:\n", missing_values)
```

```
Missing values in each column:
 Customer ID                   0
Full Name                     0
Date of Purchase              0
Age                           0
State                         0
MTN Device                    0
Gender                        0
Satisfaction Rate             0
Customer Review               0
Customer Tenure in months     0
Subscription Plan             0
Unit Price                    0
Number of Times Purchased     0
Total Revenue                 0
Data Usage                    0
Customer Churn Status         0
Reasons for Churn           690
dtype: int64
```

In [8]:
```
# Duplicate values
duplicate_values = df.duplicated().sum()
print(f"Number of duplicate rows: {duplicate_values}")
```

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

In [9]:
```python
# Check for inconsistent data
data.describe()
```

Out[9]:

	Age	Satisfaction Rate	Customer Tenure in months	Unit Price	Number of Times Purchased	Total Revenue	
count	974.000000	974.000000	974.000000	974.000000	974.000000	9.740000e+02	9
mean	48.043121	2.947639	31.422998	19196.663244	10.564682	2.046696e+05	
std	17.764307	1.384219	17.191256	25586.726985	5.709427	3.247855e+05	
min	16.000000	1.000000	1.000000	350.000000	1.000000	3.500000e+02	
25%	32.000000	2.000000	17.000000	5500.000000	5.000000	3.300000e+04	
50%	49.000000	3.000000	31.000000	14500.000000	11.000000	1.080000e+05	1
75%	63.750000	4.000000	47.000000	24000.000000	15.000000	2.610000e+05	1
max	80.000000	5.000000	60.000000	150000.000000	20.000000	3.000000e+06	2

In [10]:
```python
# Get information about the metrics (CSAT and MRR Churn)
mrr_churn = data[data['Customer Churn Status'] == 'Yes']['Total Revenue'].sum()
mrr_total = data['Total Revenue'].sum()
mrr_churn_percentage = (mrr_churn / mrr_total) * 100
print(f"Monthly Recurring Revenue (MRR) Churn: {mrr_churn_percentage:.2f}%")

csat = data['Satisfaction Rate'].value_counts()
csat_good = csat[csat.index.isin([4,5])].sum()
csat_total = data['Satisfaction Rate'].notna().sum()
csat_percentage = (csat_good / csat_total) * 100
print(f"Customer Satisfaction (CSAT): {csat_percentage:.2f}%")
```

```
Monthly Recurring Revenue (MRR) Churn: 29.09%
Customer Satisfaction (CSAT): 38.81%
```

There is nothing concerning in the data quality itself (the dataset is clean). However, from a business perspective, we should be concerned. Metrics such as MRR (Monthly Recurring Revenue) and CSAT (Customer Satisfaction Score) indicate that the business is in poor condition. Therefore, it is crucial to find a solution, starting with visualizing the data for deeper insights.

Data Understanding (Visualization)

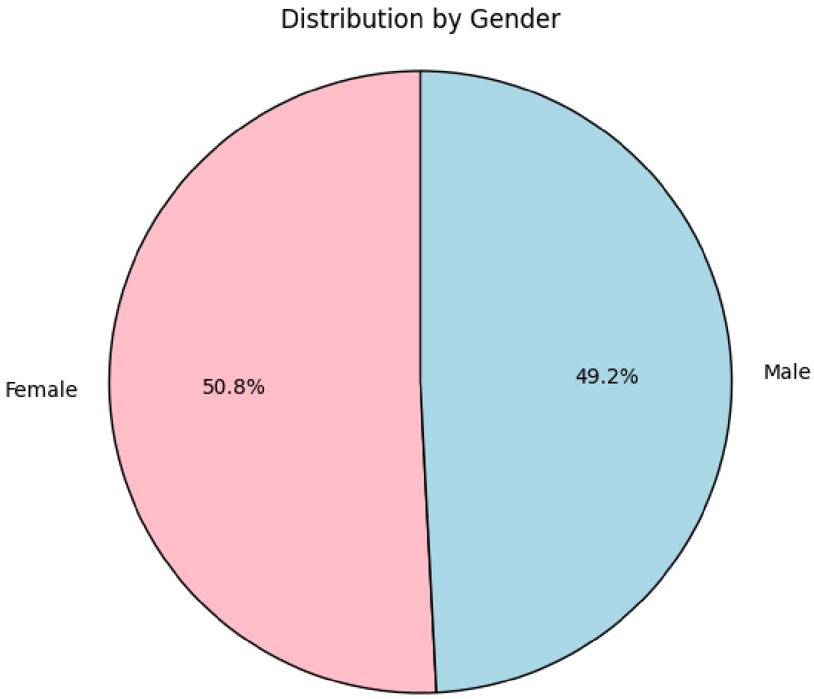
In [11]:
```python
numerical = data.select_dtypes(include=['number']).columns
data[numerical].columns
```

Out[11]:
```
Index(['Age', 'Satisfaction Rate', 'Customer Tenure in months', 'Unit Price',
       'Number of Times Purchased', 'Total Revenue', 'Data Usage'],
      dtype='object')
```

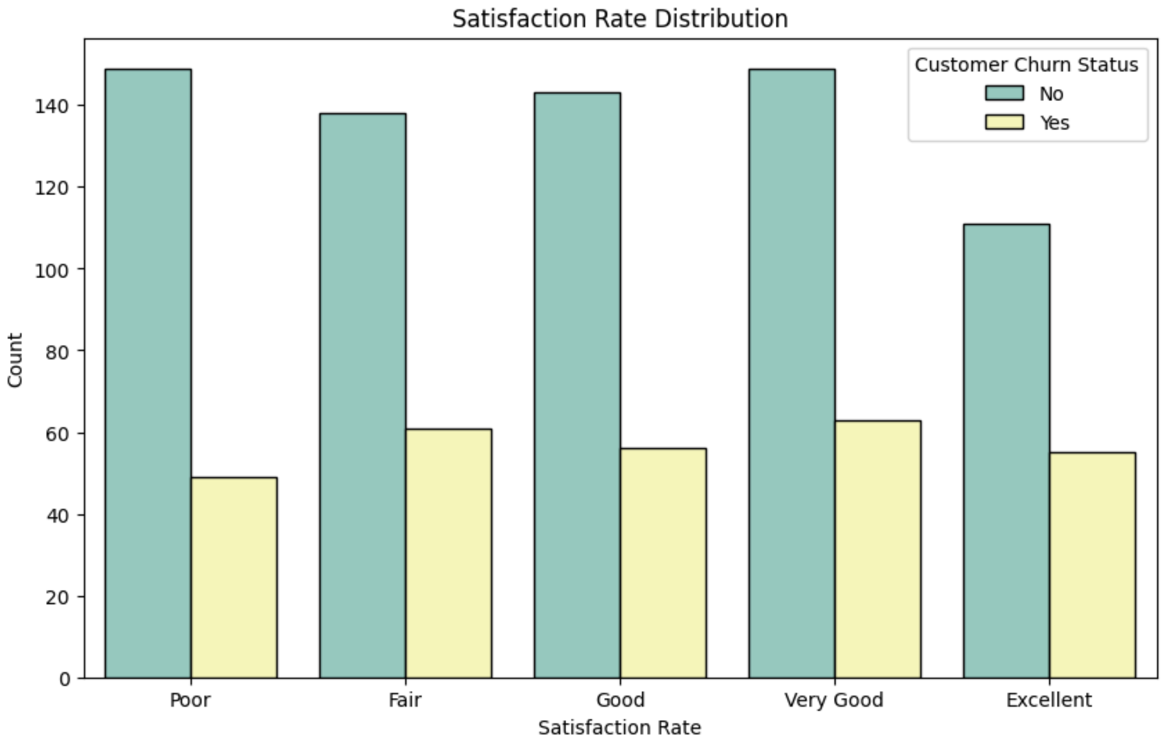
In [12]:
```python
categorical = data.select_dtypes(include=['object']).columns
data[categorical].columns
```

Out[12]: Index(['Customer ID', 'Full Name', 'Date of Purchase', 'State', 'MTN Device',
              'Gender', 'Customer Review', 'Subscription Plan',
              'Customer Churn Status', 'Reasons for Churn'],
             dtype='object')

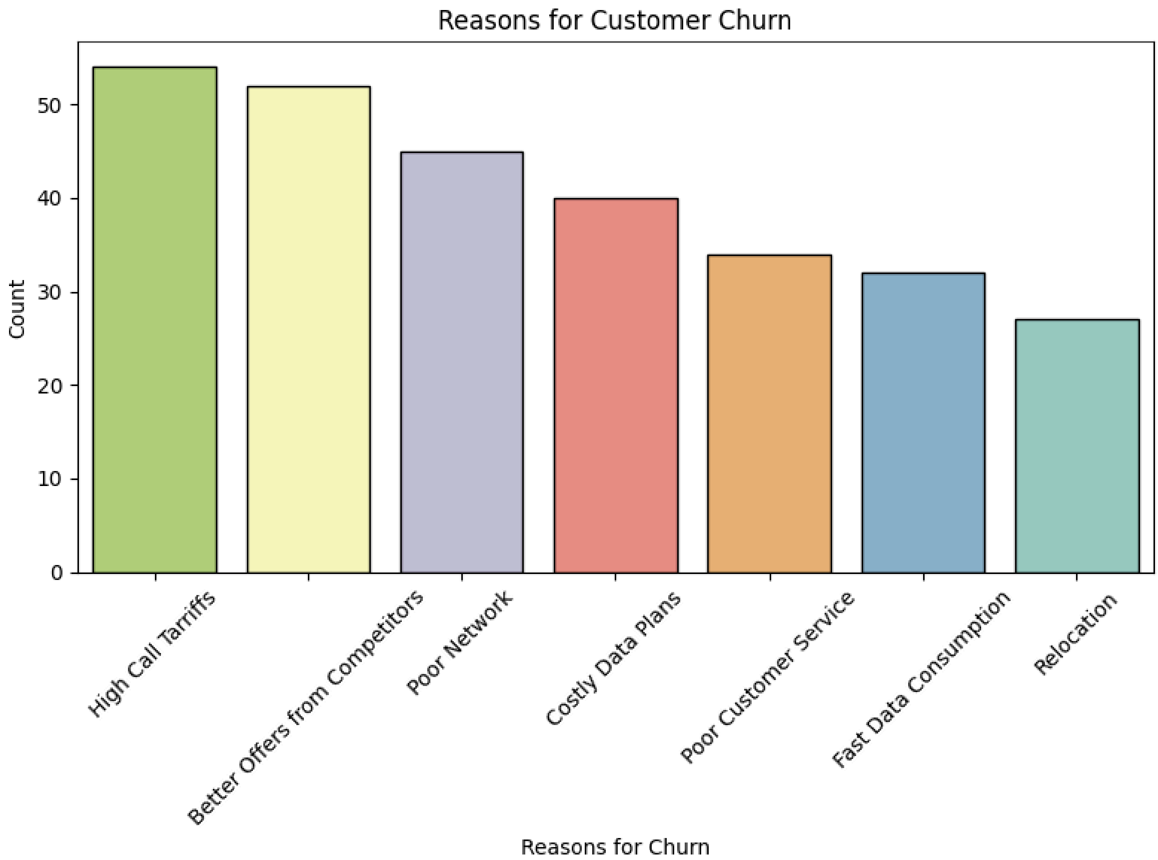
In [13]:
```
plt.figure(figsize=(10,6))
plt.pie(data['Gender'].value_counts(), labels=df['Gender'].value_counts().index,
plt.title('Distribution by Gender')
plt.axis('equal')
plt.show()
```



In [14]:
```
plt.figure(figsize=(10, 6))
sns.countplot(x='Satisfaction Rate', hue='Customer Churn Status' ,data=data, pal
plt.title('Satisfaction Rate Distribution')
plt.xlabel('Satisfaction Rate')
plt.ylabel('Count')
plt.xticks(ticks=[0, 1, 2, 3, 4], labels=["Poor", "Fair", "Good", "Very Good", "
plt.show()
```




```
In [15]: order = data[data['Customer Churn Status'] == 'Yes']['Reasons for Churn'].value_
         plt.figure(figsize=(8, 6))
         sns.countplot(data=data[data['Customer Churn Status'] == 'Yes'], x='Reasons for
         plt.title('Reasons for Customer Churn')
         plt.xlabel('Reasons for Churn')
         plt.ylabel('Count')
         plt.xticks(rotation=45)
         plt.tight_layout()
         plt.show()
```



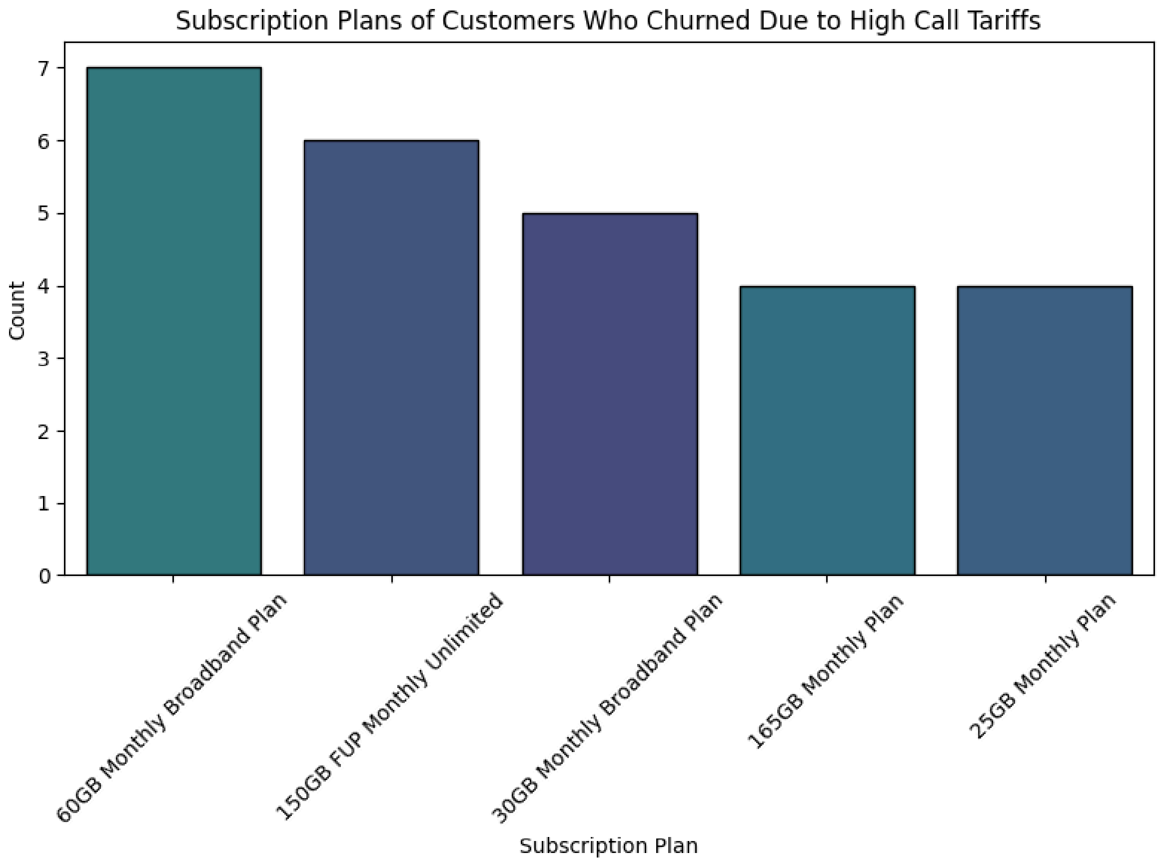
In [16]:
```python
high_call = data[data['Customer Churn Status'] == 'Yes'][data[data['Customer Chu
print(f"Number of customers who churned due to high call tariffs: {len(high_call
high_call.head(2)
```

Number of customers who churned due to high call tariffs: 54

Out[16]:

	Customer ID	Full Name	Date of Purchase	Age	State	MTN Device	Gender	Satisfaction Rate	Custo Re
183	CUST0097	Ese Perez	Feb-25	55	Zamfara	5G Broadband Router	Female	3	(
220	CUST0116	Bola Garcia	Mar-25	30	Benue	Mobile SIM Card	Male	4	(

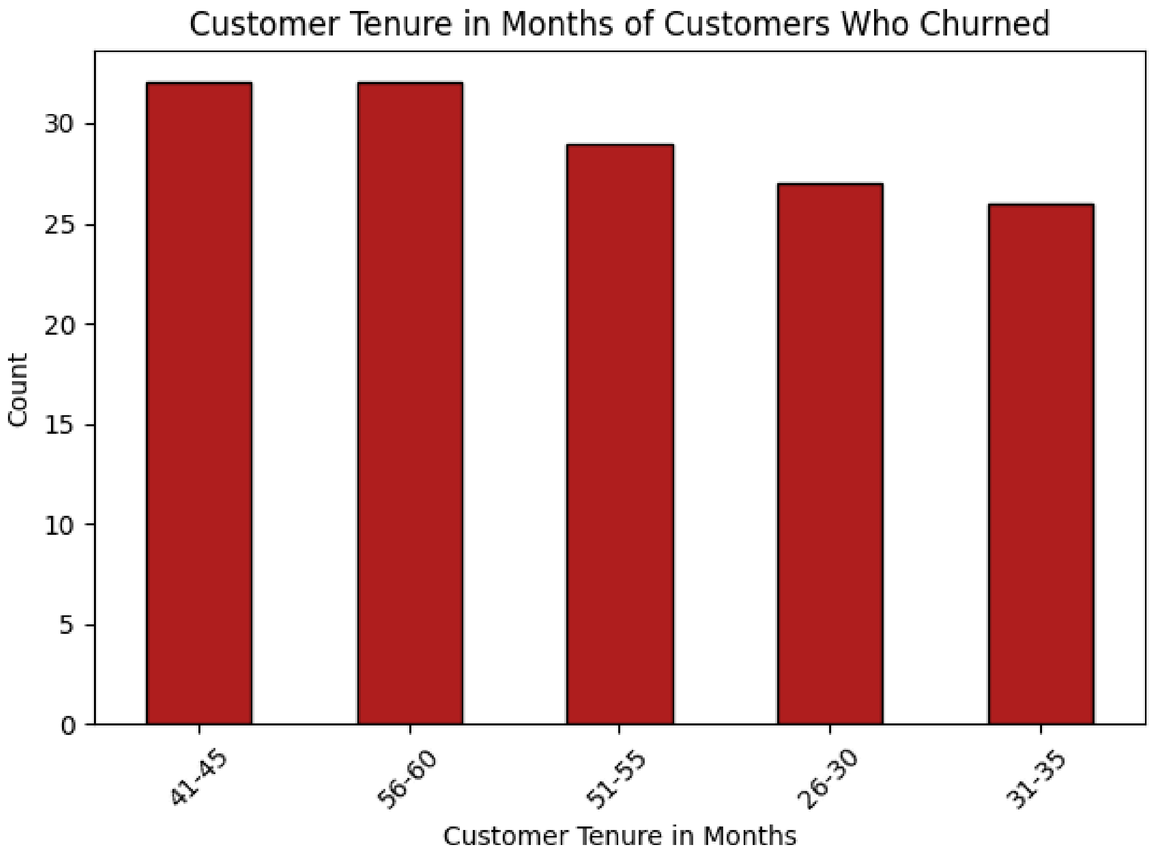
In [17]:
```python
order = high_call['Subscription Plan'].value_counts().head(5).index
plt.figure(figsize=(8, 6))
sns.countplot(data=high_call, x='Subscription Plan', hue='Subscription Plan', or
plt.title('Subscription Plans of Customers Who Churned Due to High Call Tariffs'
plt.xlabel('Subscription Plan')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [18]:
```python
bins = [0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60]
labels = ['0-5', '6-10', '11-15', '16-20', '21-25', '26-30', '31-35', '36-40', '
```

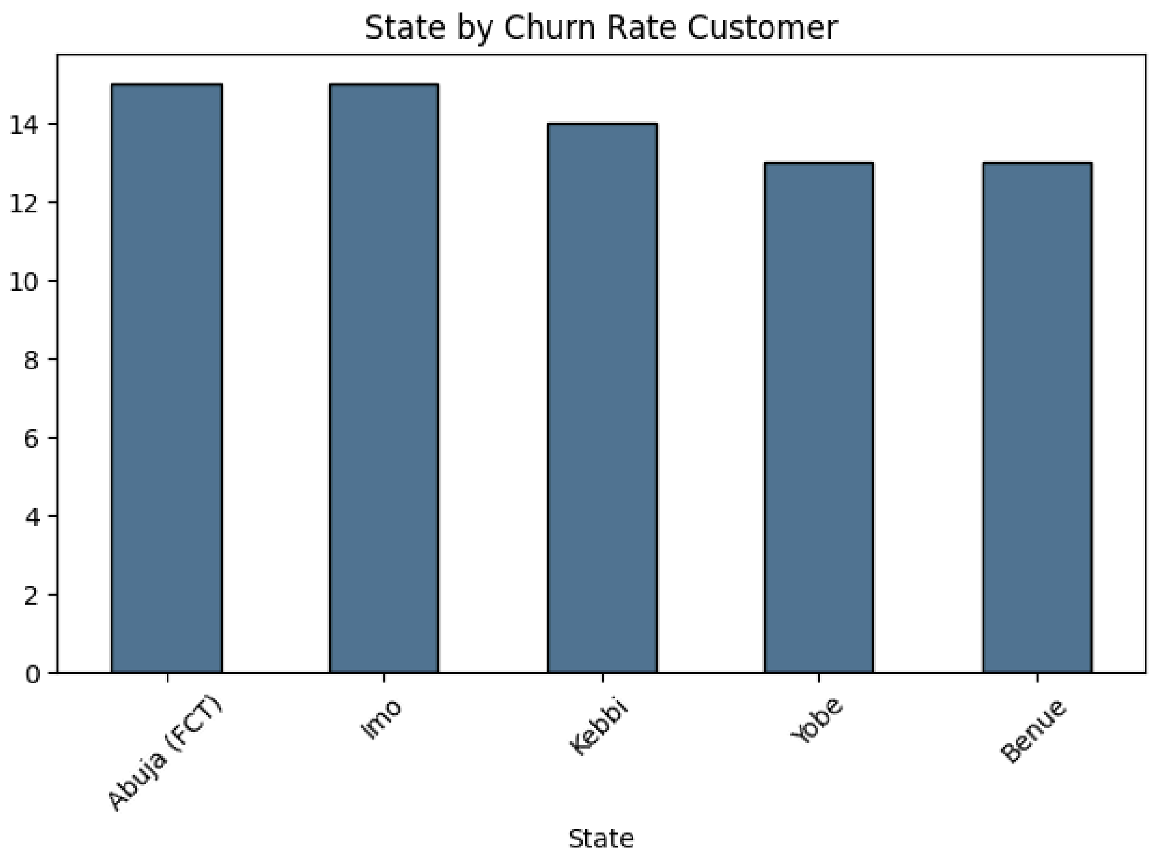
```
tenure_binned = pd.cut(data[data['Customer Churn Status'] == 'Yes']['Customer Te
```

In [19]:
```
tenure_binned.value_counts().head(5).plot(kind='bar', color='firebrick', edgecol
plt.title('Customer Tenure in Months of Customers Who Churned')
plt.xlabel('Customer Tenure in Months')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

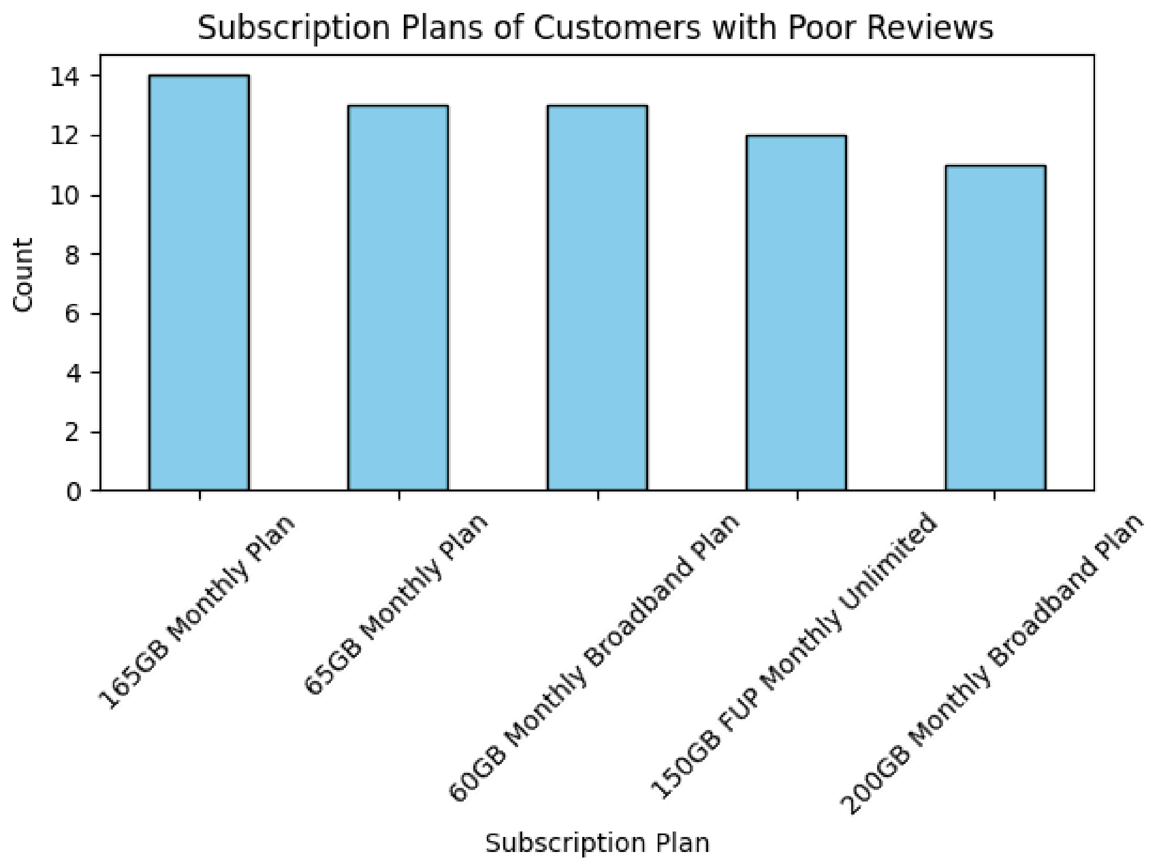


In [ ]:

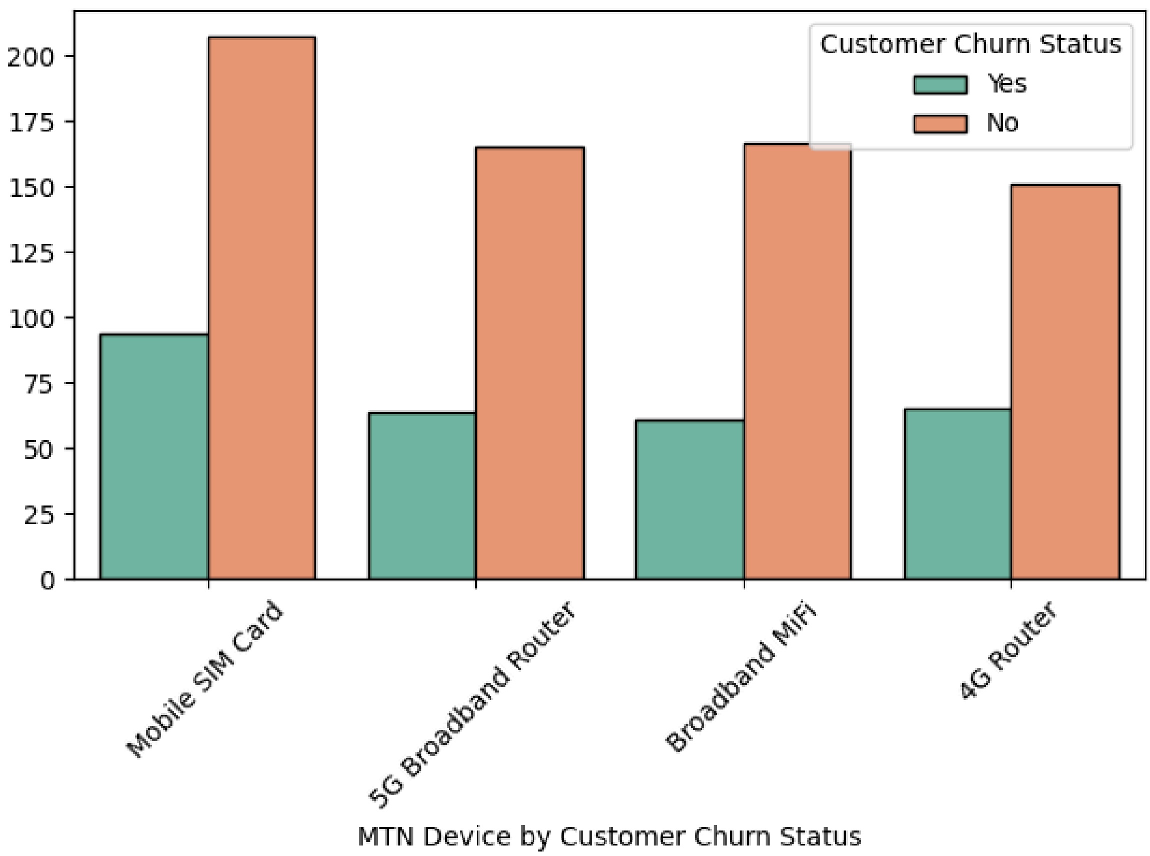
In [20]:
```
state_churn = data[data['Customer Churn Status'] == 'Yes']['State']
state_churn.columns = ['State', 'Count']
state_churn.value_counts().head(5).plot(kind='bar', color='#547792', edgecolor='
plt.xlabel('State')
plt.title("State by Churn Rate Customer")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [21]:
```
bottom_reviews = data[data['Customer Churn Status'] == 'Yes'][data[data['Custome
bottom_reviews['Subscription Plan'].value_counts().head(5).plot(kind='bar', colo
plt.title('Subscription Plans of Customers with Poor Reviews')
plt.xlabel('Subscription Plan')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



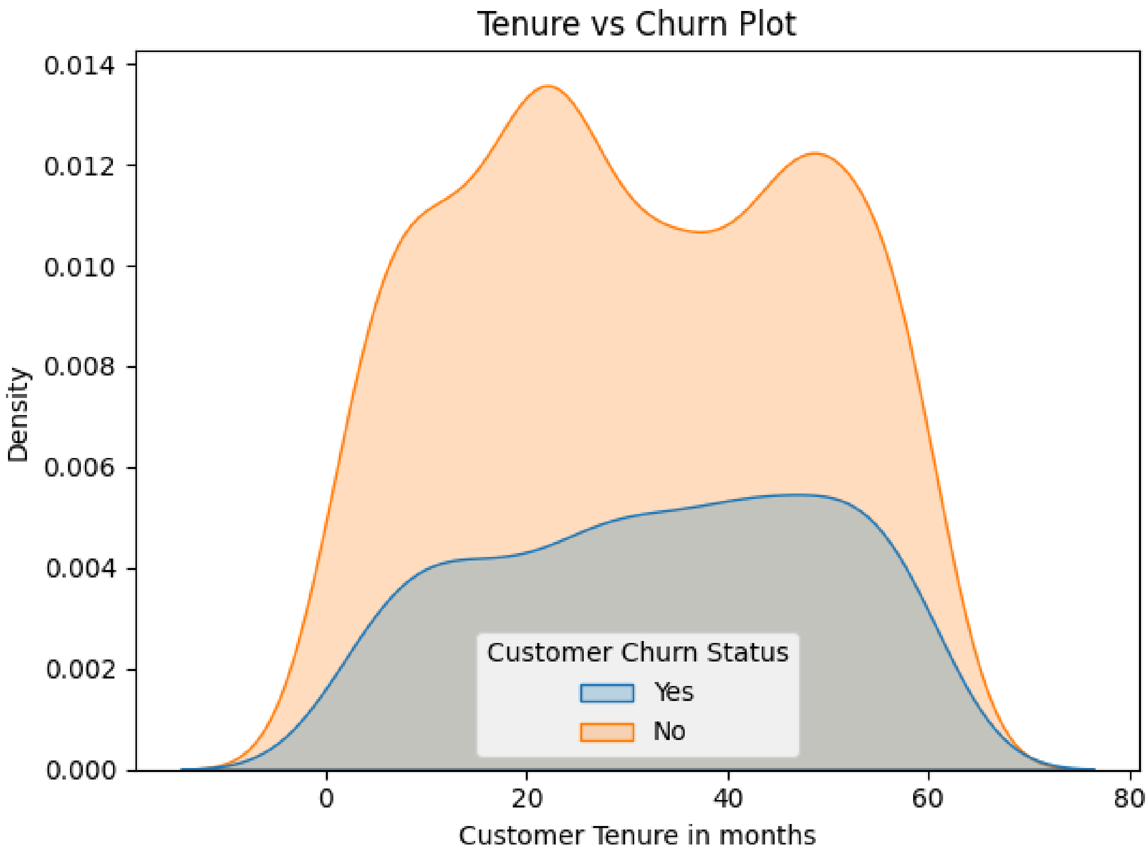
In [22]:
```
sns.countplot(data=data, hue='Customer Churn Status', x='MTN Device', order=data
plt.xlabel('MTN Device by Customer Churn Status')
plt.ylabel('')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [55]:
```
data[data['MTN Device'] == '4G Router']['Customer Churn Status'].value_counts()
```

Out[55]:
```
Customer Churn Status
No     151
Yes     65
Name: count, dtype: int64
```

In [53]:
```
sns.kdeplot(data=df, x='Customer Tenure in months', hue='Customer Churn Status',
plt.title("Tenure vs Churn Plot")
plt.tight_layout()
plt.show()
```



In [23]:
```
encoder = LabelEncoder()
data.head(2)
```

Out[23]:

	Customer ID	Full Name	Date of Purchase	Age	State	MTN Device	Gender	Satisfaction Rate	Customer Review	C T
0	CUST0001	Ngozi Berry	Jan-25	27	Kwara	4G Router	Male	2	Fair	
1	CUST0002	Zainab Baker	Mar-25	16	Abuja (FCT)	Mobile SIM Card	Female	2	Fair	

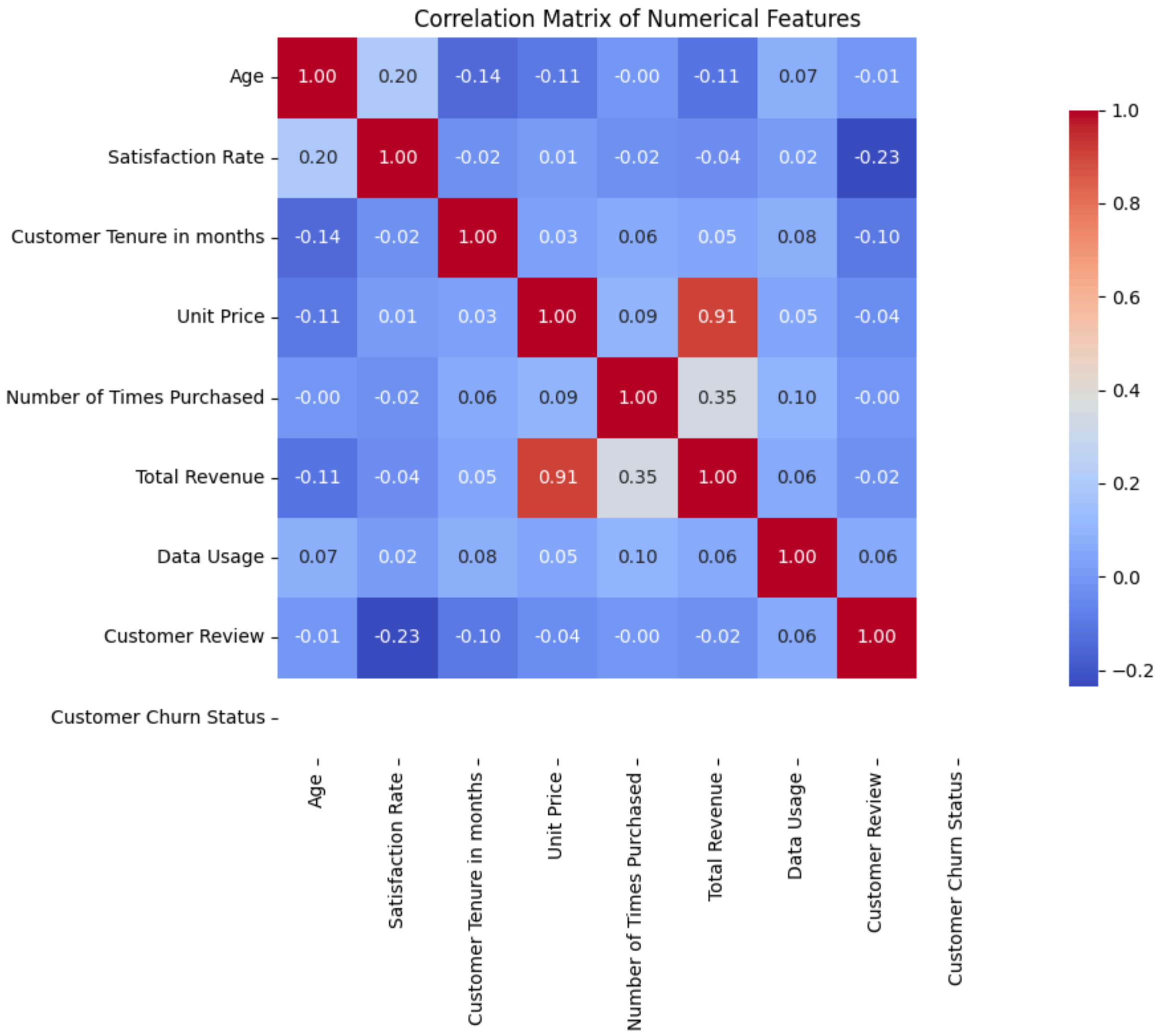
In [24]:
```
data_encode = data[["Customer Review", "Customer Churn Status"]].apply(encoder.f

data_matrix = pd.concat([data[numerical], data_encode], axis=1)
data_matrix.head()
```

Out[24]:

	Age	Satisfaction Rate	Customer Tenure in months	Unit Price	Number of Times Purchased	Total Revenue	Data Usage	Customer Review	Custom Chu Stat
0	27	2	2	35000	19	665000	44.48	1	
1	16	2	22	5500	12	66000	19.79	1	
2	21	1	60	20000	8	160000	9.64	3	
3	21	1	60	500	8	4000	197.05	3	
4	21	1	60	9000	15	135000	76.34	3	

In [25]:

```
matrix = data_matrix[data_matrix['Customer Churn Status'] == 1].corr()
plt.figure(figsize=(12, 8))
sns.heatmap(matrix, annot=True, fmt='.2f', cmap='coolwarm', square=True, cbar_kw
plt.title('Correlation Matrix of Numerical Features')
plt.tight_layout()
plt.show()
```



Machine Learning Workflow

We aim to predict customers who are at risk of churning.

In [26]:
```
data.head(2)
```

Out[26]:

	Customer ID	Full Name	Date of Purchase	Age	State	MTN Device	Gender	Satisfaction Rate	Customer Review	C T
0	CUST0001	Ngozi Berry	Jan-25	27	Kwara	4G Router	Male	2	Fair	
1	CUST0002	Zainab Baker	Mar-25	16	Abuja (FCT)	Mobile SIM Card	Female	2	Fair	

In [27]:
```
data[numerical].head(2)
```

Out[27]:

	Age	Satisfaction Rate	Customer Tenure in months	Unit Price	Number of Times Purchased	Total Revenue	Data Usage
0	27	2	2	35000	19	665000	44.48
1	16	2	22	5500	12	66000	19.79

In [28]:
```
data_numerical = data[numerical]
data_numerical = data_numerical.drop(columns=['Age', 'Number of Times Purchased'
data_numerical.head(2)
```

Out[28]:

	Satisfaction Rate	Customer Tenure in months	Unit Price	Total Revenue	Data Usage
0	2	2	35000	665000	44.48
1	2	22	5500	66000	19.79

In [29]:
```
data_encode = data[["State", "Subscription Plan", "Customer Review", "Customer C
new_data = pd.concat([data_numerical, data_encode], axis=1)
new_data.head()
```

Out[29]:

	Satisfaction Rate	Customer Tenure in months	Unit Price	Total Revenue	Data Usage	State	Subscription Plan	Customer Review	Cust
0	2	2	35000	665000	44.48	22	7	1	
1	2	22	5500	66000	19.79	1	3	1	
2	1	60	20000	160000	9.64	31	5	3	
3	1	60	500	4000	197.05	31	8	3	
4	1	60	9000	135000	76.34	31	15	3	

In [30]:
```
X_train, X_test, y_train, y_test = train_test_split(new_data.drop(columns=['Cust
```

In [31]:
```
def evaluate_model(model, X_train, y_train, X_test, y_test):
    cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
    selector = RFECV(estimator=model, step=1, cv=cv, scoring='accuracy')
    selector.fit(X_train, y_train)
    selected_features = X_train.columns[selector.support_]
    X_train_sel = X_train[selected_features]
    X_test_sel = X_test[selected_features]
    final_model = model
    final_model.fit(X_train_sel, y_train)
    score = final_model.score(X_test_sel, y_test)
    return score

def evaluate_model_2(model, X_train, y_train, X_test, y_test):
    selector = SelectKBest(score_func=f_classif, k='all')
    selector.fit(X_train, y_train)
    selected_features = X_train.columns[selector.get_support()]
    X_train_sel = X_train[selected_features]
    X_test_sel = X_test[selected_features]
    final_model = model
    final_model.fit(X_train_sel, y_train)
    score = final_model.score(X_test_sel, y_test)
    return score
```

In [32]:
```
model_dt = DecisionTreeClassifier(random_state=42)

score = evaluate_model(model_dt, X_train, y_train, X_test, y_test)
print(f"Decision Tree Classifier Accuracy: {score:.2f}")
```

```
Decision Tree Classifier Accuracy: 0.62
```

In [33]:
```
model_rf = RandomForestClassifier(random_state=42)

score = evaluate_model(model_rf,  X_train, y_train, X_test, y_test)
print(f"Random Forest Classifier Accuracy: {score:.2f}")
```

```
Random Forest Classifier Accuracy: 0.71
```

In [34]:
```
model_gbc = GradientBoostingClassifier(n_estimators=100, random_state=42)

score = evaluate_model_2(model_gbc,  X_train, y_train, X_test, y_test)
print(f"Random Gradient Boosting Classifier Accuracy: {score:.2f}")
```

```
Random Gradient Boosting Classifier Accuracy: 0.71
```

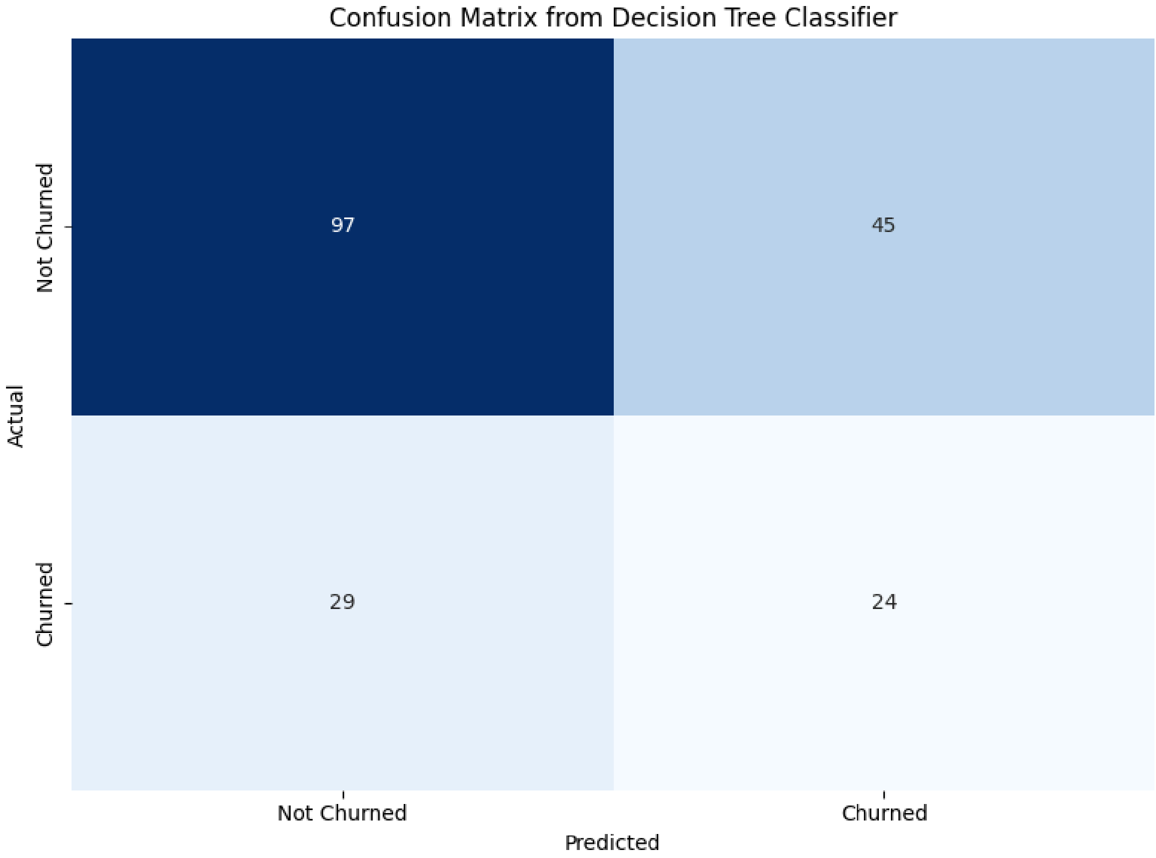
In [35]:
```
model_knn = KNeighborsClassifier(n_neighbors=5)

score = evaluate_model_2(model_knn,  X_train, y_train, X_test, y_test)
print(f"Random KNN Accuracy: {score:.2f}")
```

```
Random KNN Accuracy: 0.73
```

Evaluation Model

In [36]:
```
cm_dt = confusion_matrix(y_test, model_dt.predict(X_test))
plt.figure(figsize=(8, 6))
sns.heatmap(cm_dt, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=['
plt.title('Confusion Matrix from Decision Tree Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

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



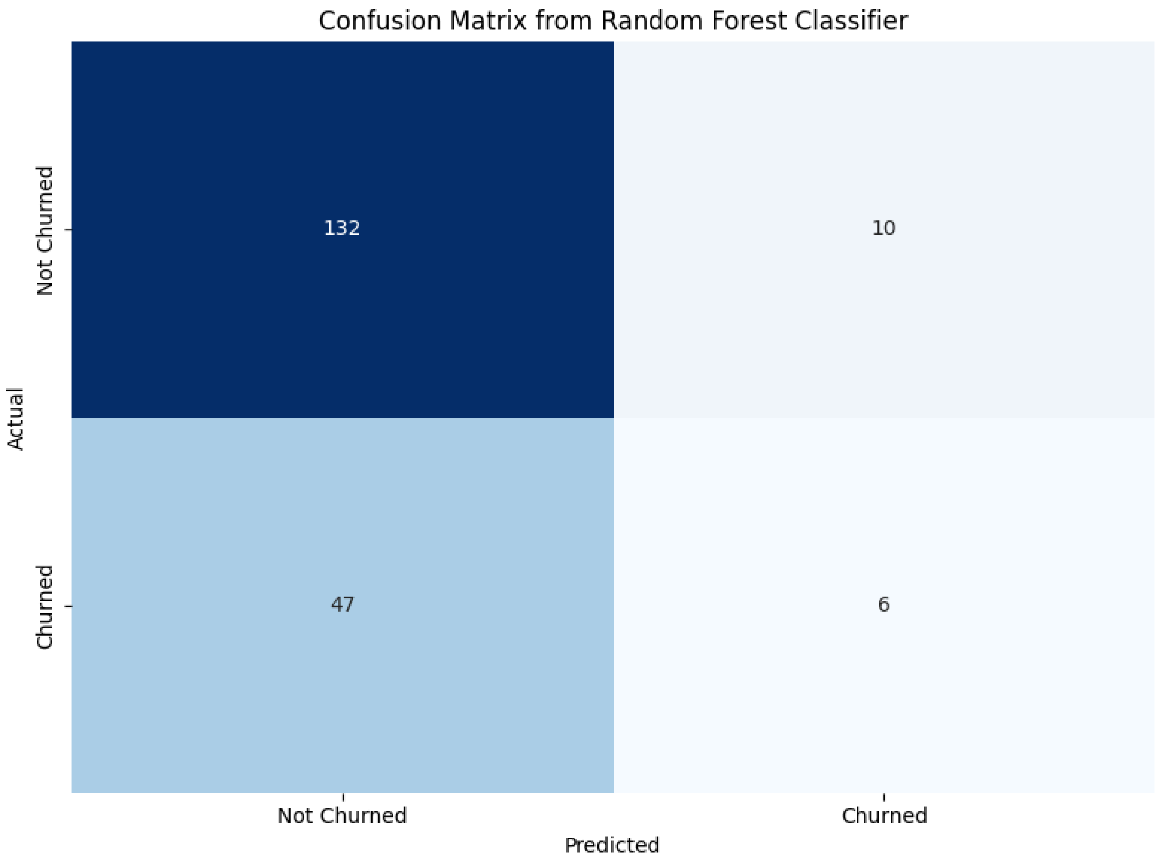
In [37]:

```
recall_churn_dt = cm_dt[1, 1] / (cm_dt[1, 1] + cm_dt[1, 0])
precision_churn_dt = cm_dt[1, 1] / (cm_dt[1, 1] + cm_dt[0, 1])
f1_churn_dt = 2 * (recall_churn_dt * precision_churn_dt) / (recall_churn_dt + pr

print("Decision Tree Classifier Metrics:")
print("----------------------------------")
print(f"Recall for Churned Customers: {recall_churn_dt:.2f}")
print(f"Precision for Churned Customers: {precision_churn_dt:.2f}")
print(f"F1 Score for Churned Customers: {f1_churn_dt:.2f}")
```

```
Decision Tree Classifier Metrics:
----------------------------------
Recall for Churned Customers: 0.45
Precision for Churned Customers: 0.35
F1 Score for Churned Customers: 0.39
```

In [38]:

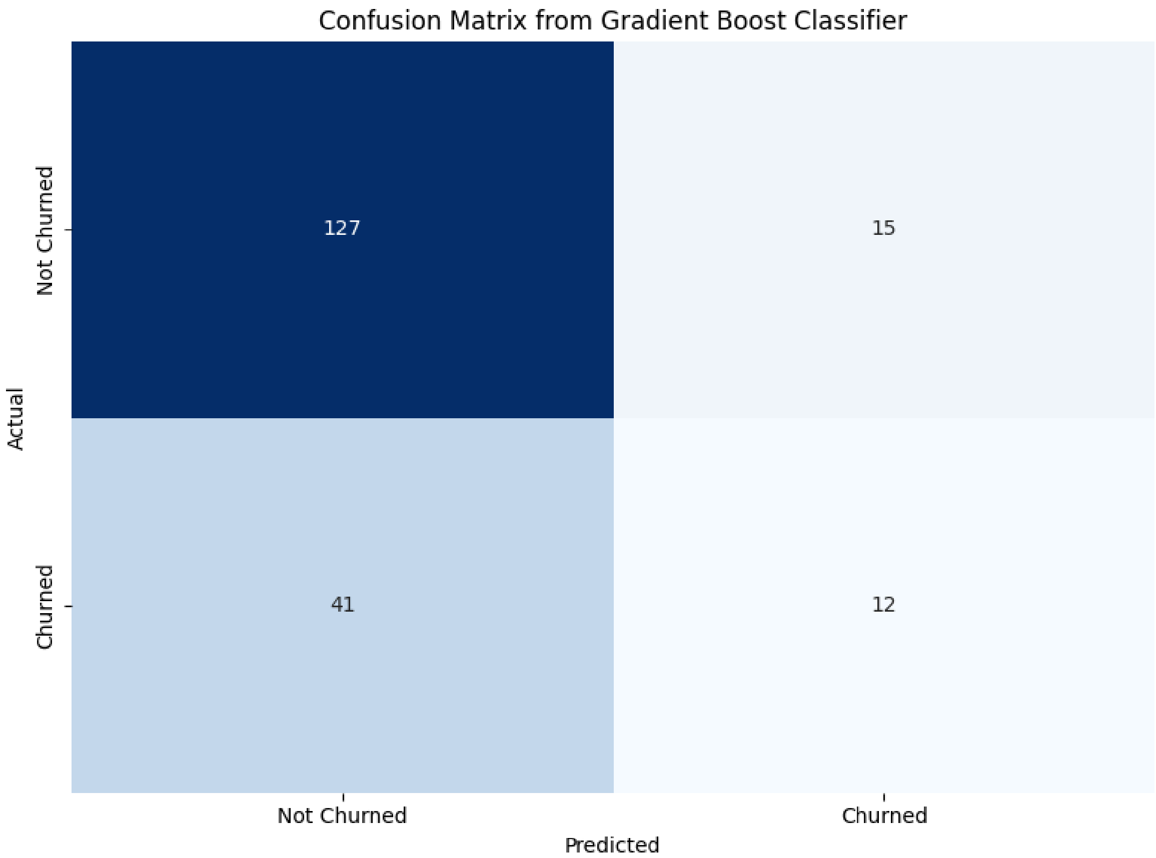
```
cm_rf = confusion_matrix(y_test, model_rf.predict(X_test))
plt.figure(figsize=(8, 6))
sns.heatmap(cm_rf, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=['
plt.title('Confusion Matrix from Random Forest Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()
```



In [39]:
```
recall_churn_rf = cm_rf[1, 1] / (cm_rf[1, 1] + cm_rf[1, 0])
precision_churn_rf = cm_rf[1, 1] / (cm_rf[1, 1] + cm_rf[0, 1])
f1_churn_rf = 2 * (recall_churn_rf * precision_churn_rf) / (recall_churn_rf + pr

print("Random Forest Classifier Metrics:")
print("----------------------------------")
print(f"Recall for Churned Customers: {recall_churn_rf:.2f}")
print(f"Precision for Churned Customers: {precision_churn_rf:.2f}")
print(f"F1 Score for Churned Customers: {f1_churn_rf:.2f}")
```

```
Random Forest Classifier Metrics:
----------------------------------
Recall for Churned Customers: 0.11
Precision for Churned Customers: 0.38
F1 Score for Churned Customers: 0.17
```

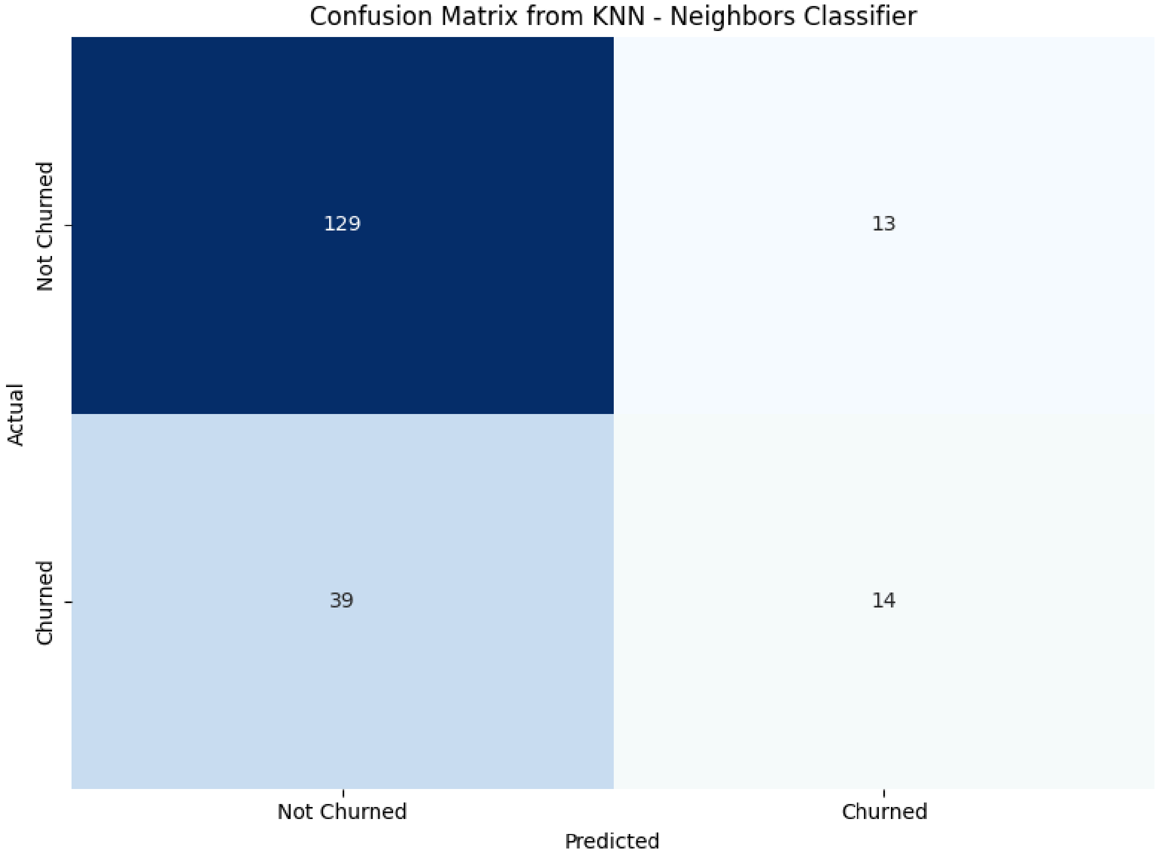
In [40]:
```
cm_gbc = confusion_matrix(y_test, model_gbc.predict(X_test))
plt.figure(figsize=(8, 6))
sns.heatmap(cm_gbc, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=[
plt.title('Confusion Matrix from Gradient Boost Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()
```



In [41]:
```
recall_churn_gbc = cm_gbc[1, 1] / (cm_gbc[1, 1] + cm_gbc[1, 0])
precision_churn_gbc = cm_gbc[1, 1] / (cm_gbc[1, 1] + cm_gbc[0, 1])
f1_churn_gbc = 2 * (recall_churn_gbc * precision_churn_gbc) / (recall_churn_gbc

print("Gradient Boost Classifier Metrics:")
print("---------------------------------")
print(f"Recall for Churned Customers: {recall_churn_gbc:.2f}")
print(f"Precision for Churned Customers: {precision_churn_gbc:.2f}")
print(f"F1 Score for Churned Customers: {f1_churn_gbc:.2f}")
```

```
Gradient Boost Classifier Metrics:
---------------------------------
Recall for Churned Customers: 0.23
Precision for Churned Customers: 0.44
F1 Score for Churned Customers: 0.30
```

In [42]:
```
cm_knn = confusion_matrix(y_test, model_knn.predict(X_test))
plt.figure(figsize=(8, 6))
sns.heatmap(cm_knn, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=[
plt.title('Confusion Matrix from KNN - Neighbors Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()
```



In [43]:
```
recall_churn_knn = cm_knn[1, 1] / (cm_knn[1, 1] + cm_knn[1, 0])
precision_churn_knn = cm_knn[1, 1] / (cm_knn[1, 1] + cm_knn[0, 1])
f1_churn_knn = 2 * (recall_churn_knn * precision_churn_knn) / (recall_churn_knn

print("KNN Classifier Metrics:")
print("-----------------------")
print(f"Recall for Churned Customers: {recall_churn_knn:.2f}")
print(f"Precision for Churned Customers: {precision_churn_knn:.2f}")
print(f"F1 Score for Churned Customers: {f1_churn_knn:.2f}")
```

```
KNN Classifier Metrics:
-----------------------
Recall for Churned Customers: 0.26
Precision for Churned Customers: 0.52
F1 Score for Churned Customers: 0.35
```

Prediction

We will chose Decision Tree as the base model for our approach. Why? Because our primary goal is to quickly identify users who are likely to churn (Decision tree has higher Recall compared to other models). Even if the model misclassifies some retained users as potential churners, it's acceptable. Our objective is to retain as many users as possible.

While this approach may lead to an increase in marketing costs due to targeting users who may not actually churn, it can still effectively help reduce the overall churn rate. Our target is to bring the current churn rate down from 29% to below the 21% industry benchmark.

In [44]:
```
def predict_churn(model, x_sample):
    y_sample = model.predict([x_sample])
```

```
    return y_sample
```

In [47]:
```
random_number = random.randrange(1,len(X_test)-1)
x_sample = X_test.iloc[random_number]
y_sample = y_test.iloc[random_number]
print(f"Sample Data:\n{x_sample}\n")
print(f"Sample Data Churn Status: {y_sample}\n")
```

```
Sample Data:
Satisfaction Rate              4.00
Customer Tenure in months     32.00
Unit Price                 35000.00
Total Revenue              70000.00
Data Usage                   187.96
State                         14.00
Subscription Plan              7.00
Customer Review                4.00
Name: 539, dtype: float64

Sample Data Churn Status: 1
```

In [48]:
```
warnings.filterwarnings("ignore", category=UserWarning)
prediction = predict_churn(model_dt, x_sample)
if prediction[0] == 1:
    print("🚨 Risk Alert: This customer is likely to churn.")
    print("Recommended Strategy: Proactively reach out with a personalized reten
else:
    print("✅ Customer Retention Likely.")
    print("Recommended Strategy: Maintain engagement with regular updates and va
```

```
🚨 Risk Alert: This customer is likely to churn.
Recommended Strategy: Proactively reach out with a personalized retention offer o
r exclusive service benefits.
```

What insights did we get?

After conducting data exploration and visualization, here are some important findings that can be used as strategic considerations for companies:

1. The difference in churn rate between male and female customers does not show a significant gap. **This suggests that gender is not the main cause of churn and does not need to be prioritized in retention strategies.**

2. Customers who gave Very Good reviews actually contributed the highest churn rate, followed by Fair, Good, and finally Poor. This opens up two possibilities.

   - Customers with good scores (Very Good/Good) keep switching because the competitor's program is more attractive.
   - Poor reviews are very few because it is likely that customers are very disappointed and immediately churn without giving feedback.

   Recommendation: Conduct a follow-up survey of churn customers who previously gave high ratings to explore the main reasons for their move.

3. The main reason for customer churn is calling rates that are perceived as expensive. The top three products most often associated with churn due to this are:

- 60GB Monthly Broadband Plan.
- 150GB FUP Monthly Unlimited.
- 30GB Monthly Broadband Plan.

Recommendation: Reevaluate the pricing structure and benefits of these three plans, and compare them with competitors. If necessary, consider relaunching with new, more competitive benefits.

4. The tenure range with the most churn is between 41-60 months. This suggests that:

   - Existing customers can start to feel bored, disappointed, or tempted by competitors' offerings.
   - The current loyalty program may not be effective enough.

   Recommendation: Create a special retention strategy for existing customers, such as loyalty rewards, exclusive discounts, or special offers to extend the subscription period.

5. There are 3 regions that should be concerned to reduce the churn rate, namely Abuja (FCT), Imo, and Kebbi. **A deeper analysis needs to be done as to why these three regions account for the largest churn rate**.

6. Subscribers with Mobile SIM Card devices do account for the largest churn in absolute terms, which is reasonable considering the number of users is much higher than other devices. However, for 4G Router devices, although the total number of users is only around 216, there are around 65 customers who churn, which is equivalent to a 30% churn rate. This is a fairly high churn rate for one type of device.
   Recommendation: Conduct an in-depth analysis of the 4G Router's user experience - such as network speed, stability, plan price, or after-sales service - to determine whether the product is still worth maintaining, upgrading, or needs to be adjusted to a new market strategy.

Most churn is caused by price and customer perception of service value. To reduce churn, it is important that companies not only focus on acquiring new customers, but also strengthen the value proposition and loyalty of existing customers.

> **Disclaimer:** ***The analysis and insights in this project were prepared as part of a personal data analysis and business skills development exercise. The data used is from open sources. Each insight aims to exercise an analytical mindset and is not intended as a professional business recommendation.***