Predicting Customer Churn: Identifying Customers Susceptible to Churn

Overview

This project aims to develop a machine learning model to predict customer churn for Reder Telecom. By leveraging customer data such as demographics, engagement, and feedback, we can identify which customers are likely to churn and take proactive actions to retain them.

Rationale for the Project

Customer churn has become a significant challenge for telecom companies, including Reder Telecom. Churn refers to when customers stop using a service, and it is essential to predict which customers are at risk of churning to implement effective retention strategies. Understanding churn can help reduce operational costs, improve customer satisfaction, and increase profitability.

Aim of the Project

The primary goal of this project is to:

- Build a machine learning model to predict customer churn.
- Identify the key drivers of churn by analyzing customer behavior and attributes.

Data Description

Dataset Overview

The dataset used in this project contains both categorical and numerical features, capturing customer demographics, behavior, service interactions, and their relationship with the telecom service. This rich dataset provides insights that help predict customer churn.

Feature	Description	Data Type

Feature	Description	Data Type	
Customer ID	Unique identifier for each customer.	Categorical	
Name	Name of the customer.	Categorical	
Age	Age of the customer.	Numerical	
Gender	Gender of the customer.	Categorical	
Location	The city or region where the customer is based.	Categorical	
Email	Customer's email address for communication.	Categorical	john@examp
Phone	Customer's phone number.	Categorical	
Address	The physical postal address of the customer.	Categorical	
Segment	Customer segment (e.g., premium, regular) based on their behavior and purchases.	Categorical	
Purchase History	A record of customer purchases, including product names, purchase frequency, and value.	Structured	100}, ...]| | **Service Interactions** | The history of the customer's interactions with customer service (e.g., calls, chats). | S | **Payment History** | A record of the customer's payment method, amount, and any issues with payments.

Feature	Description	Data Type
Website Usage	Data on the customer's engagement with the company's website (e.g., page views, time spent).	Structured
Clickstream Data	A record of customer interactions with the website, including clicks, searches, and actions.	Structured
Engagement Metrics	Metrics like number of logins and frequency of interaction (e.g., daily, weekly, monthly).	Structured
Feedback	Customer feedback, including ratings (1-5) and any comments provided.	Categorical
Marketing Communication	Record of marketing emails sent, opened, and clicked by the customer.	Structured
NPS (Net Promoter Score)	A score between 0-10 reflecting customer satisfaction and loyalty.	Numerical

Feature	Description	Data Type
Churn Label	Binary label indicating if the customer churned (1 = Yes, 0 = No).	Categorical
Timestamp	The date and time when the data was recorded.	Datetime

Tech Stack

The project utilizes the following tools and libraries:

- **Python**: Primary programming language.
- **Pandas**: Data manipulation and analysis.
- **NumPy**: Numerical operations.
- **Matplotlib & Seaborn**: Data visualization.
- **Scikit-learn**: Machine learning model building.

In [35]:
```
## Import Neccesary Libraries
from ast import literal_eval
import pandas as pd
import numpy as np  # Changed py to np for consistency with numpy
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, Confus
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')
```

Data Collection

In [2]:
```
###Loading the dataset
df = pd.read_excel('Dataset.xlsx')
```

Data Exploration

In Data Exploration, we will be looking at:

- Understanding the data structure, Statistics, quality of the dataset
- Visualizing the data to gain insights
- Checking for missing vlues

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

Out[3]:

	CustomerID	Name	Age	Gender	Location	Email	Phone	Address	Segment	Pu
0	1001	Mark Barrett	31	Male	Andrewfort	allison74@example.net	3192528777	61234 Shelley Heights Suite 467\nCohentown, GU...	Segment B	'
1	1002	Jeremy Welch	66	Female	Millerhaven	fmiller@example.com	231-587-1818x8651	4959 Jennifer Junction\nNew Angelaport, TN 87397	Segment C	
2	1003	Brandon Patel	36	Female	Lozanostad	jasonbrown@example.org	(270)633-9095	38701 Amanda Brook Apt. 076\nKimshire, NJ 62516	Segment B	'
3	1004	Tina Martin	62	Female	South Dustin	matthew62@example.net	050.081.8706x11982	67324 Ashley Coves\nSouth John, RI 29650	Segment C	
4	1005	Christopher Rodriguez	68	Female	West James	shannonstrickland@example.org	+1-701-854-4915x724	01169 Miller Mission\nWest Anthonyburgh, WY 47359	Segment C	Cr

5 rows × 21 columns

In [4]:
```
### Checking For Missing values
df.isnull().sum()
```

Out[4]:
```
CustomerID              0
Name                    0
Age                     0
Gender                  0
Location                0
Email                   0
Phone                   0
Address                 0
Segment                 0
PurchaseHistory         0
SubscriptionDetails     0
ServiceInteractions     0
PaymentHistory          0
WebsiteUsage            0
ClickstreamData         0
EngagementMetrics       0
Feedback                0
MarketingCommunication  0
NPS                     0
ChurnLabel              0
Timestamp               0
dtype: int64
```

In [5]:
```
### Check for duplicates
df.duplicated().any()
```

Out[5]:
```
False
```

Get a Statiscal Overview of numerical columns in the datasets

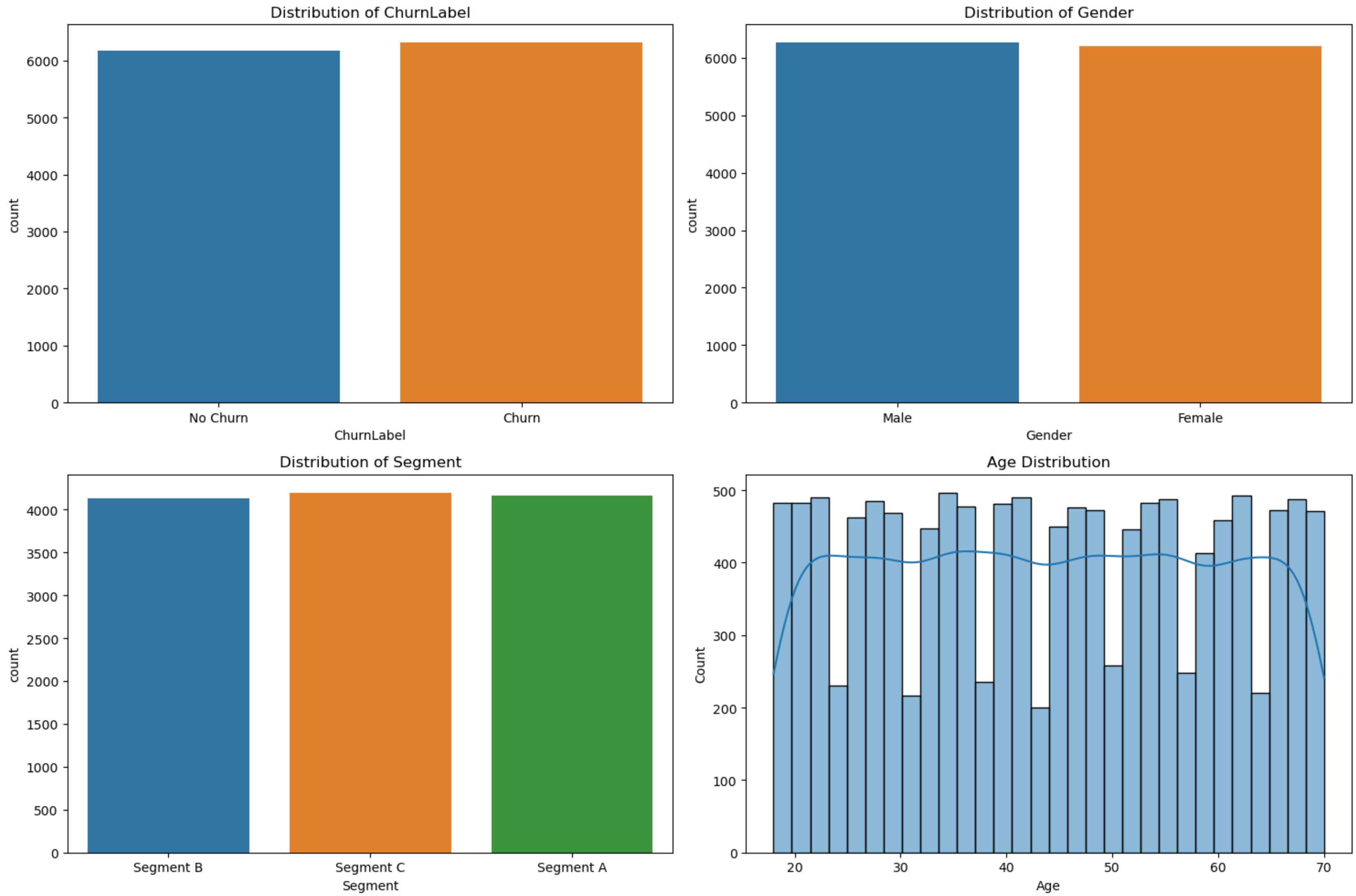
In [6]:
```
starts_overview = df.describe()
starts_overview
```

Out[6]:

	CustomerID	Age	NPS	ChurnLabel
count	12483.00000	12483.000000	12483.000000	12483.000000
mean	7242.00000	43.930065	2.973884	0.505808
std	3603.67604	15.341521	2.644623	0.499986
min	1001.00000	18.000000	0.000000	0.000000
25%	4121.50000	31.000000	1.000000	0.000000
50%	7242.00000	44.000000	2.000000	1.000000
75%	10362.50000	57.000000	4.000000	1.000000
max	13483.00000	70.000000	9.000000	1.000000

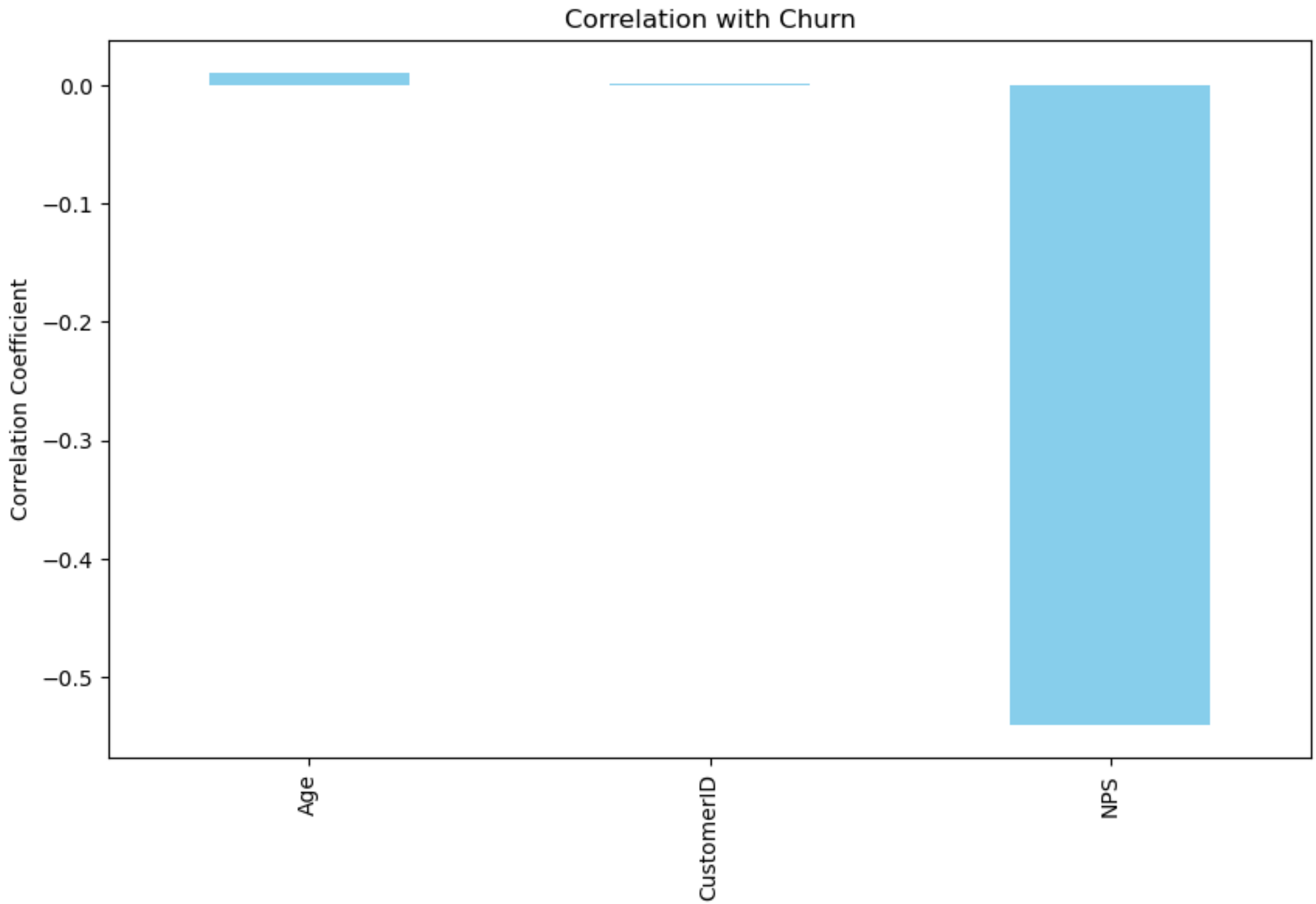
Next, we see how target variable 'ChurnLabel', and some of other variables are distributed.

In [7]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Setup the figure and axes
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(15, 10))

# plot the distribution of the target variable ChurnLabel
sns.countplot(x="ChurnLabel", data=df, ax=ax[0,0])
ax[0,0].set_title('Distribution of ChurnLabel')
ax[0,0].set_xticklabels(['No Churn', 'Churn'])

# plot distribution of Gender
sns.countplot(x="Gender", data=df, ax=ax[0,1])
ax[0,1].set_title('Distribution of Gender')

# plot distribution of Segment
sns.countplot(x="Segment", data=df, ax=ax[1,0])
ax[1,0].set_title('Distribution of Segment')

# plot distribution of Age
sns.histplot(df['Age'], bins=30, ax=ax[1,1], kde=True)
ax[1,1].set_title('Age Distribution')

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



Correlation Analysis: Which columns in the dataset corelates with the 'Churnlabel' column

In [8]:
```
## Calculate correlation with ChurnLabel
correlation = df.select_dtypes(include=np.number).corr()['ChurnLabel'].sort_values(ascending=False)

# plot the correlation
plt.figure(figsize= (10,6))
correlation.drop('ChurnLabel').plot(kind='bar', color='skyblue')
plt.title('Correlation with Churn')
plt.ylabel('Correlation Coefficient')
plt.show()

correlation
```



Out[8]:
```
ChurnLabel    1.000000
Age           0.010273
CustomerID    0.001530
NPS          -0.540703
Name: ChurnLabel, dtype: float64
```

Nested columns and see how they react

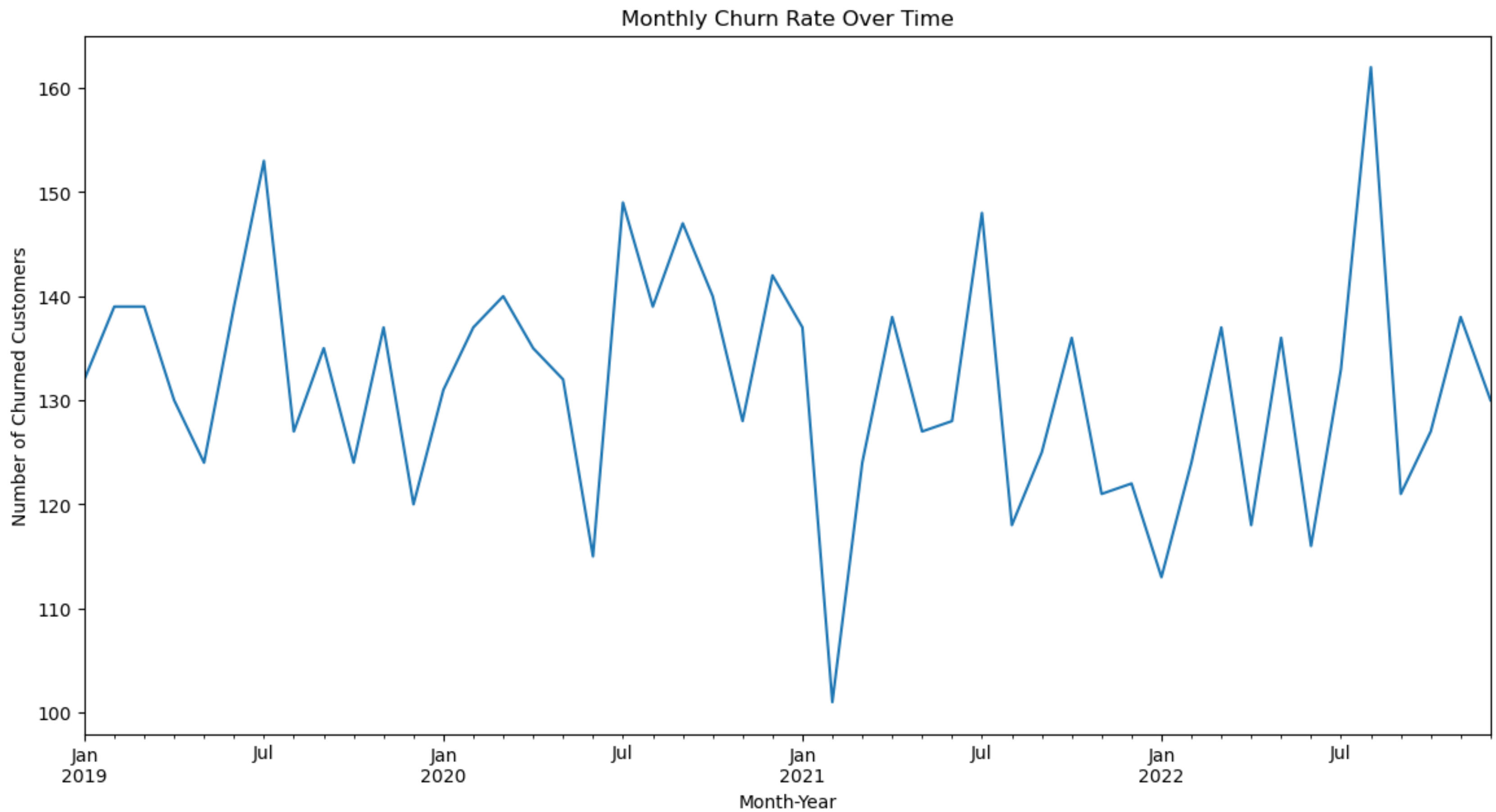
In [9]:
```
# List out all the nested columns
nested_colums = [
    'PurchaseHistory',
    'SubscriptionDetails',
    'ServiceInteractions',
    'PaymentHistory',
    'WebsiteUsage',
    'ClickstreamData',
    'EngagementMetrics',
    'Feedback',
    'MarketingCommunication'
]

# Ensure that df exists and contains the nested columns
w1, w2 = 25, 1000
for col in nested_colums:  # Corrected spelling
    row = [col, df[col][0]]
    print('\n| {:<{w1}} | {:<{w2}} |'.format(*row, w1=w1, w2=w2))
```

```
| PurchaseHistory           | [{'Product': 'Frozen Cocktail Mixes', 'Frequency': 8, 'Value': 884.43}, {'Prod
uct': 'Printer, Copier & Fax Machine Accessories', 'Frequency': 7, 'Value': 397.14}, {'Product': 'Hockey Sti
ck Care', 'Frequency': 10, 'Value': 498.92}, {'Product': 'Guacamole', 'Frequency': 2, 'Value': 718.43}, {'Pr
oduct': 'Mortisers', 'Frequency': 2, 'Value': 614.08}, {'Product': 'Rulers', 'Frequency': 6, 'Value': 221.6
8}, {'Product': 'Invitations', 'Frequency': 3, 'Value': 660.04}]
|

| SubscriptionDetails       | {'Plan': 'Express', 'Start_Date': '2020-06-08', 'End_Date': '2022-10-27'}
|

| ServiceInteractions       | [{'Type': 'Call', 'Date': '2019-09-26'}, {'Type': 'Chat', 'Date': '2021-07-2
5'}, {'Type': 'Email', 'Date': '2020-04-13'}, {'Type': 'Chat', 'Date': '2020-11-15'}]
|

| PaymentHistory            | [{'Method': 'Credit Card', 'Late_Payments': 5}, {'Method': 'PayPal', 'Late_Pay
ments': 11}, {'Method': 'Bank Transfer', 'Late_Payments': 24}]
|

| WebsiteUsage              | {'PageViews': 49, 'TimeSpent(minutes)': 15}
|

| ClickstreamData           | [{'Action': 'Add to Cart', 'Page': 'register', 'Timestamp': '2020-09-13 17:0
6:44'}, {'Action': 'Search', 'Page': 'login', 'Timestamp': '2022-03-30 14:51:52'}, {'Action': 'Click', 'Page
': 'about', 'Timestamp': '2019-11-10 05:48:48'}, {'Action': 'Add to Cart', 'Page': 'terms', 'Timestamp': '20
19-05-15 10:17:44'}, {'Action': 'Add to Cart', 'Page': 'author', 'Timestamp': '2022-07-14 03:40:53'}, {'Acti
on': 'Search', 'Page': 'main', 'Timestamp': '2019-01-13 08:39:42'}, {'Action': 'Add to Cart', 'Page': 'faq',
'Timestamp': '2019-02-19 05:28:25'}, {'Action': 'Add to Cart', 'Page': 'about', 'Timestamp': '2020-11-01 2
0:59:55'}, {'Action': 'Click', 'Page': 'faq', 'Timestamp': '2021-12-22 16:39:40'}, {'Action': 'Add to Cart',
'Page': 'main', 'Timestamp': '2020-11-11 03:25:36'}, {'Action': 'Click', 'Page': 'privacy', 'Timestamp': '20
21-06-13 06:18:41'}, {'Action': 'Add to Cart', 'Page': 'search', 'Timestamp': '2022-03-28 16:25:35'}, {'Acti
on': 'Search', 'Page': 'homepage', 'Timestamp': '2019-09-26 12:27:42'}, {'Action': 'Click', 'Page': 'search'
, 'Timestamp': '2021-03-31 16:35:39'}, {'Action': 'Search', 'Page': 'main', 'Timestamp': '2021-12-22 10:02:1
9'}, {'Action': 'Search', 'Page': 'about', 'Timestamp': '2019-08-24 05:11:40'}, {'Action': 'Add to Cart', 'P
age': 'index', 'Timestamp': '2021-04-30 00:38:03'}, {'Action': 'Search', 'Page': 'privacy', 'Timestamp': '20
21-06-21 16:23:49'}, {'Action': 'Search', 'Page': 'about', 'Timestamp': '2022-04-03 07:25:20'}, {'Action': '
Search', 'Page': 'author', 'Timestamp': '2022-11-07 02:24:31'}, {'Action': 'Search', 'Page': 'about', 'Times
tamp': '2019-08-25 17:37:59'}, {'Action': 'Search', 'Page': 'post', 'Timestamp': '2020-12-18 01:36:34'}, {'A
ction': 'Search', 'Page': 'home', 'Timestamp': '2021-11-24 07:33:26'}, {'Action': 'Search', 'Page': 'login',
'Timestamp': '2020-11-15 07:21:21'}] |
```

```
| EngagementMetrics         | {'Logins': 19, 'Frequency': 'Weekly'}
|

| Feedback                  | {'Rating': 1, 'Comment': 'I move baby go small big. Office institution six. Fa
ct until hear technology right company seek.'}
|

| MarketingCommunication    | [{'Email_Sent': '2019-10-17', 'Email_Opened': '2022-01-12', 'Email_Clicked':
'2022-11-27'}, {'Email_Sent': '2019-10-17', 'Email_Opened': '2022-01-12', 'Email_Clicked': '2022-11-27'},
{'Email_Sent': '2019-10-17', 'Email_Opened': '2022-01-12', 'Email_Clicked': '2022-11-27'}, {'Email_Sent': '2
019-10-17', 'Email_Opened': '2022-01-12', 'Email_Clicked': '2022-11-27'}, {'Email_Sent': '2019-10-17', 'Emai
l_Opened': '2022-01-12', 'Email_Clicked': '2022-11-27'}, {'Email_Sent': '2019-10-17', 'Email_Opened': '202
2-01-12', 'Email_Clicked': '2022-11-27'}, {'Email_Sent': '2019-10-17', 'Email_Opened': '2022-01-12', 'Email_
Clicked': '2022-11-27'}, {'Email_Sent': '2019-10-17', 'Email_Opened': '2022-01-12', 'Email_Clicked': '2022-1
1-27'}]
|
```

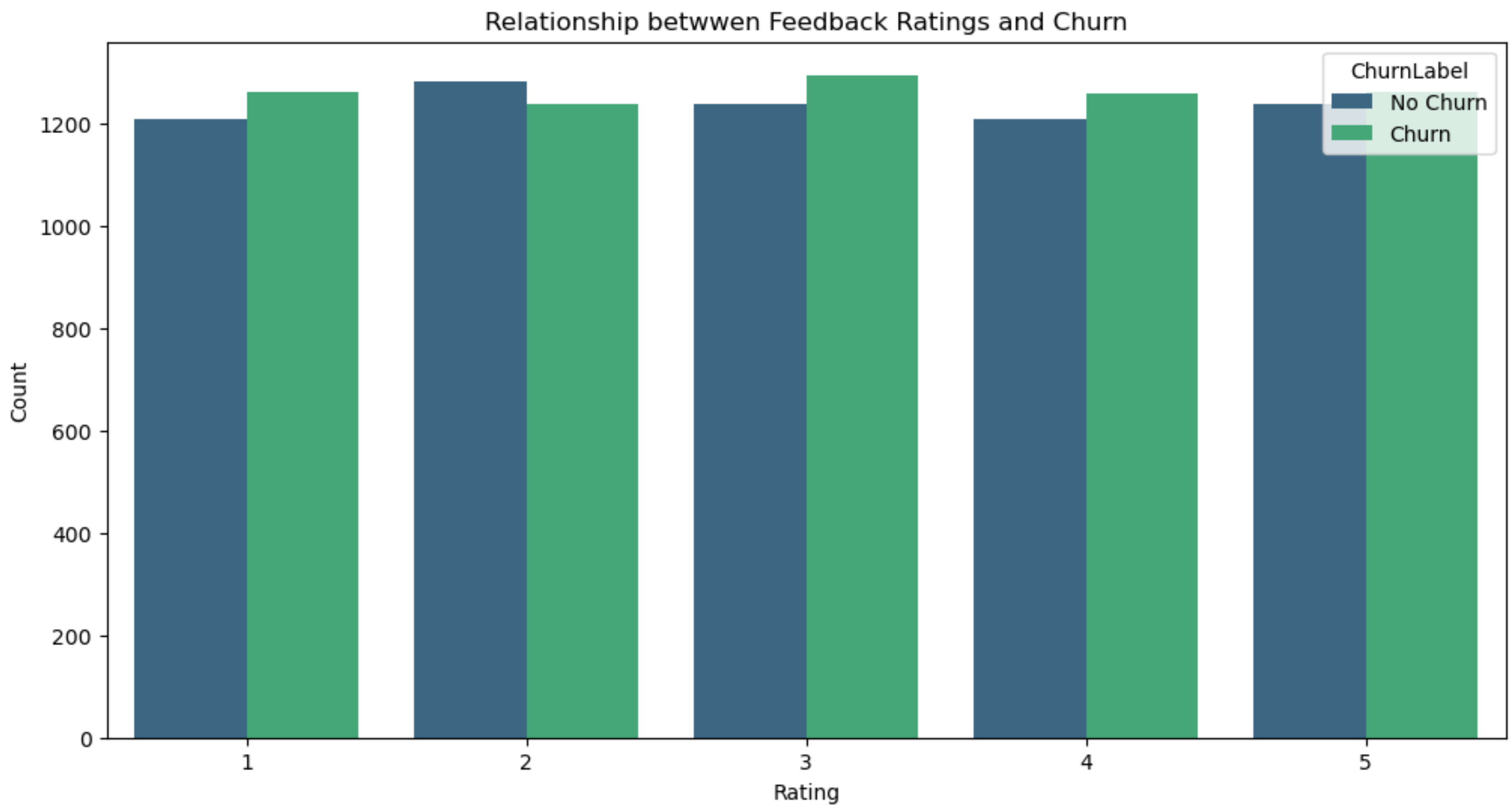
Temporal Analysis:

In [10]:
```
#Convert the Timestamp to datatime format so that it can be
df['Timestamp'] = pd.to_datetime(df['Timestamp'])

#Extract the month-year from the Timestamp
df['MonthYear'] = df['Timestamp'].dt.to_period('M')

#Group by MonthYear and calculat the churn rates
monthly_churn_rate = df.groupby('MonthYear')['ChurnLabel'].sum()

#Plot the churn raete over time
plt.figure(figsize=(14,7))
monthly_churn_rate.plot()
plt.title('Monthly Churn Rate Over Time')
plt.ylabel('Number of Churned Customers')
plt.xlabel('Month-Year')
plt.show()
```



Customer feedback "Rating and the ChurnLabel"

In [11]:
```
# Extracting rating from the feedback column and creating a new column for it
df['FeedbackRating'] = df['Feedback'].apply(lambda x: eval(x)['Rating'])

#Plotting the relationship between between
plt.figure(figsize=(12, 6))
sns.countplot(x= 'FeedbackRating', data=df, hue='ChurnLabel', palette='viridis')
plt.title('Relationship betwwen Feedback Ratings and Churn')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.legend(title='ChurnLabel', loc='upper right', labels=['No Churn', 'Churn'])
plt.show()
```



From the visual, there doesn't seem to be any indication that the "Feedback" rating affects the "ChurnLabel"

Data Preprocessing and Feature Engineering

Here we will do:

- Create new feature that may have predictive power
- Convert categorical variables to numeric variables, using encoding technique scale or normalize numeric variables if necessary,
- Split the data into training and testing subsets,
- remove irrelevant features.

we begin by converting nested values from string formats to list/dictionaries using "literal_eval" function

In [12]:
```
# List nested column
nested_columns = [
    'PurchaseHistory',
    'SubscriptionDetails',
    'ServiceInteractions',
    'PaymentHistory',
    'WebsiteUsage',
    'ClickstreamData',
    'EngagementMetrics',
    'Feedback',
    'MarketingCommunication'
]

# Apply the literal_eval function
for feature in nested_columns:
    df[feature] = df[feature].apply(literal_eval)
```

More features will be extravted from the dataset.

In [13]:
```
# PurchaseHistory
df['PurchasedProducts'] = df['PurchaseHistory'].apply(lambda x: '|'.join([i['Product'] for i in x]))
df['PurchaseFrequency'] = df['PurchaseHistory'].apply(lambda x: sum([i['Frequency'] for i in x]))
df['PurchaseValue'] = df['PurchaseHistory'].apply(lambda x: sum([i['Value'] for i in x]))

# SubscriptionsDetails
df['SubscriptionPlan'] = df['SubscriptionDetails'].apply(lambda x: x['Plan'])
df['SubscriptionStartDate'] = df['SubscriptionDetails'].apply(lambda x: x['Start_Date'])
df['SubscriptionEndDate'] = df['SubscriptionDetails'].apply(lambda x: x['End_Date'])
df['SubscriptionDuration'] = (pd.to_datetime(df['SubscriptionEndDate']) - pd.to_datetime(df['SubscriptionStar

# WebsiteUsage
df['WebsitePageViews'] = df['WebsiteUsage'].apply(lambda x: x['PageViews'])
df['WebsiteTimeSpent'] = df['WebsiteUsage'].apply(lambda x: x['TimeSpent(minutes)'])

# EngagementMetrics
df['EngagementMetricsLogins'] = df['EngagementMetrics'].apply(lambda x: x['Logins'])
df['EngagementMetricsFrequency'] = df['EngagementMetrics'].apply(lambda x: x['Frequency'])

# Feedback
df['FeedbackRating'] = df['Feedback'].apply(lambda x: x['Rating'])
df['FeedbackComment'] = df['Feedback'].apply(lambda x: x['Comment'])

# MarketingCommunication
df['MarketingCommunicationNoOfEmails'] = df['MarketingCommunication'].apply(lambda x: len(x))

# Handling possible missing or null values during date calculations
df['MarketingCommunicationOpenClickDiff'] = df['MarketingCommunication'].apply(
    lambda x: np.mean([
        (pd.to_datetime(i['Email_Clicked']) - pd.to_datetime(i['Email_Opened'])).days
        for i in x if pd.notnull(i['Email_Clicked']) and pd.notnull(i['Email_Opened'])
    ])
)

df['MarketingCommunicationSentOpenDiff'] = df['MarketingCommunication'].apply(
    lambda x: np.mean([
        (pd.to_datetime(i['Email_Opened']) - pd.to_datetime(i['Email_Sent'])).days
        for i in x if pd.notnull(i['Email_Opened']) and pd.notnull(i['Email_Sent'])
    ])
)
```

Special Extraction from three Columns:

- Service Interactions
- PaymentHistory
- ClickstreamData

In [14]:
```
# Get all unique ServiceInteraction 'Types'
service_interaction_types = df['ServiceInteractions'].apply(lambda x: list(set([i['Type'] for i in x])))
service_interaction_types = service_interaction_types.to_list()
unique_service_interaction_type = []

# Extend the list and then make it unique after the loop
for i in service_interaction_types:
    unique_service_interaction_type.extend(i)

# Now make the list unique by converting to a set and back to a list
unique_service_interaction_type = list(set(unique_service_interaction_type))

print('All unique Service Interaction Types:', unique_service_interaction_type)

# Get all unique PaymentHistory 'Method'
payment_history_methods = df['PaymentHistory'].apply(lambda x: list(set([i['Method'] for i in x])))
payment_history_methods = payment_history_methods.to_list()
unique_payment_history_methods = []

for i in payment_history_methods:
    unique_payment_history_methods.extend(i)

# Now make the list unique by converting to a set and back to a list
unique_payment_history_methods = list(set(unique_payment_history_methods))

print('All unique Payment History Methods:', unique_payment_history_methods)

# Get all unique ClickstreamData 'Action'
clickstream_Data_actions = df['ClickstreamData'].apply(lambda x: list(set([i['Action'] for i in x])))
clickstream_Data_actions = clickstream_Data_actions.to_list()
unique_clickstream_Data_actions = []

for i in clickstream_Data_actions:
    unique_clickstream_Data_actions.extend(i)

# Now make the list unique by converting to a set and back to a list
unique_clickstream_Data_actions = list(set(unique_clickstream_Data_actions))

print('All unique Clickstream Data Actions:', unique_clickstream_Data_actions)
```

```
All unique Service Interaction Types: ['Chat', 'Call', 'Email']
All unique Payment History Methods: ['Bank Transfer', 'PayPal', 'Credit Card']
All unique Clickstream Data Actions: ['Add to Cart', 'Click', 'Search']
```

From these three columns, we're going to be encoding more.

In [15]:
```
# Define unique values for ServiceInteractions and ClickstreamData

# Assuming 'ServiceInteractions' is a column containing lists of dictionaries with a 'Type' key
unique_service_interaction_type = set(
    interaction['Type'] for interactions in df['ServiceInteractions'] for interaction in interactions
)

# Assuming 'ClickstreamData' is a column containing lists of dictionaries with an 'Action' key
unique_clickstreams_data_actions = set(
    action['Action'] for actions in df['ClickstreamData'] for action in actions
)

# ServiceInteractions
for usit in unique_service_interaction_type:
    df[f'ServiceInteractions_{usit}'] = df['ServiceInteractions'].apply(
        lambda x: len([i for i in x if i['Type'] == usit])
    )

# PaymentHistory
df['PaymentHistoryNoOfLatePayments'] = df['PaymentHistory'].apply(
    lambda x: sum(i['Late_Payments'] for i in x)
)
df['PaymentHistoryNoAvgNoOfLatePayments'] = df['PaymentHistory'].apply(
    lambda x: np.mean([i['Late_Payments'] for i in x])
)

# ClickStreamData
for ucda in unique_clickstreams_data_actions:
    df[f'ClickstreamData_{ucda}'] = df['ClickstreamData'].apply(
        lambda x: len([i for i in x if i['Action'] == ucda])
    )
```

In [16]:

```
df.head()
```

Out[16]:

	CustomerID	Name	Age	Gender	Location	Email	Phone	Address	Segment	Pu
0	1001	Mark Barrett	31	Male	Andrewfort	allison74@example.net	3192528777	61234 Shelley Heights Suite 467\nCohentown, GU...	Segment B	'
1	1002	Jeremy Welch	66	Female	Millerhaven	fmiller@example.com	231-587-1818x8651	4959 Jennifer Junction\nNew Angelaport, TN 87397	Segment C	
2	1003	Brandon Patel	36	Female	Lozanostad	jasonbrown@example.org	(270)633-9095	38701 Amanda Brook Apt. 076\nKimshire, NJ 62516	Segment B	'
3	1004	Tina Martin	62	Female	South Dustin	matthew62@example.net	050.081.8706x11982	67324 Ashley Coves\nSouth John, RI 29650	Segment C	
4	1005	Christopher Rodriguez	68	Female	West James	shannonstrickland@example.org	+1-701-854-4915x724	01169 Miller Mission\nWest Anthonyburgh, WY 47359	Segment C	Cr

5 rows × 46 columns

See all the columns

In [17]:
```
df.columns
```

Out[17]:
```
Index(['CustomerID', 'Name', 'Age', 'Gender', 'Location', 'Email', 'Phone',
       'Address', 'Segment', 'PurchaseHistory', 'SubscriptionDetails',
       'ServiceInteractions', 'PaymentHistory', 'WebsiteUsage',
       'ClickstreamData', 'EngagementMetrics', 'Feedback',
       'MarketingCommunication', 'NPS', 'ChurnLabel', 'Timestamp', 'MonthYear',
       'FeedbackRating', 'PurchasedProducts', 'PurchaseFrequency',
       'PurchaseValue', 'SubscriptionPlan', 'SubscriptionStartDate',
       'SubscriptionEndDate', 'SubscriptionDuration', 'WebsitePageViews',
       'WebsiteTimeSpent', 'EngagementMetricsLogins',
       'EngagementMetricsFrequency', 'FeedbackComment',
       'MarketingCommunicationNoOfEmails',
       'MarketingCommunicationOpenClickDiff',
       'MarketingCommunicationSentOpenDiff', 'ServiceInteractions_Chat',
       'ServiceInteractions_Call', 'ServiceInteractions_Email',
       'PaymentHistoryNoOfLatePayments', 'PaymentHistoryNoAvgNoOfLatePayments',
       'ClickstreamData_Add to Cart', 'ClickstreamData_Click',
       'ClickstreamData_Search'],
      dtype='object')
```

Pick out some columns next

In [18]:
```
df_ = df[[
    'Age',
    'Gender',
    'NPS',
    'ChurnLabel',
    'PurchaseFrequency',
    'PurchaseValue',
    'SubscriptionPlan',
    'WebsitePageViews',
    'WebsiteTimeSpent',
    'EngagementMetricsLogins',
    'EngagementMetricsFrequency',
    'FeedbackRating',
    'MarketingCommunicationNoOfEmails',
    'MarketingCommunicationOpenClickDiff',
    'MarketingCommunicationSentOpenDiff',
    'ServiceInteractions_Call',
    'ServiceInteractions_Email',
    'ServiceInteractions_Chat',
    'PaymentHistoryNoOfLatePayments',
    'ClickstreamData_Click',
    'ClickstreamData_Add to Cart',
    'ClickstreamData_Search',
    'SubscriptionDuration'


]]

df_.head()
```

Out[18]:

	Age	Gender	NPS	ChurnLabel	PurchaseFrequency	PurchaseValue	SubscriptionPlan	WebsitePageViews	WebsiteTimeSpent	Engag
0	31	Male	3	1	38	3994.72	Express	49	15	
1	66	Female	6	0	4	2844.35	Pro	100	9	
2	36	Female	3	0	14	1866.52	Essential	1	97	
3	62	Female	1	1	28	1378.64	Smart	25	31	
4	68	Female	3	0	39	2425.05	Basic	77	51	

5 rows × 23 columns

Lets See the names of the columns

In [19]:
```
df_.loc[0]
```

Out[19]:
```
Age                                     31
Gender                                Male
NPS                                      3
ChurnLabel                               1
PurchaseFrequency                       38
PurchaseValue                      3994.72
SubscriptionPlan                   Express
WebsitePageViews                        49
WebsiteTimeSpent                        15
EngagementMetricsLogins                 19
EngagementMetricsFrequency          Weekly
FeedbackRating                           1
MarketingCommunicationNoOfEmails         8
MarketingCommunicationOpenClickDiff  319.0
MarketingCommunicationSentOpenDiff   818.0
ServiceInteractions_Call                 1
ServiceInteractions_Email                1
ServiceInteractions_Chat                 2
PaymentHistoryNoOfLatePayments          40
ClickstreamData_Click                    4
ClickstreamData_Add to Cart              8
ClickstreamData_Search                  12
SubscriptionDuration                   871
Name: 0, dtype: object
```

Lets Check for Number of unique values

In [20]:
```
print('Total dataset length:', len(df_))

df_[['Gender', 'SubscriptionPlan', 'EngagementMetricsFrequency']].nunique()
```

```
Total dataset length: 12483
```

Out[20]:
```
Gender                         2
SubscriptionPlan              20
EngagementMetricsFrequency     3
dtype: int64
```

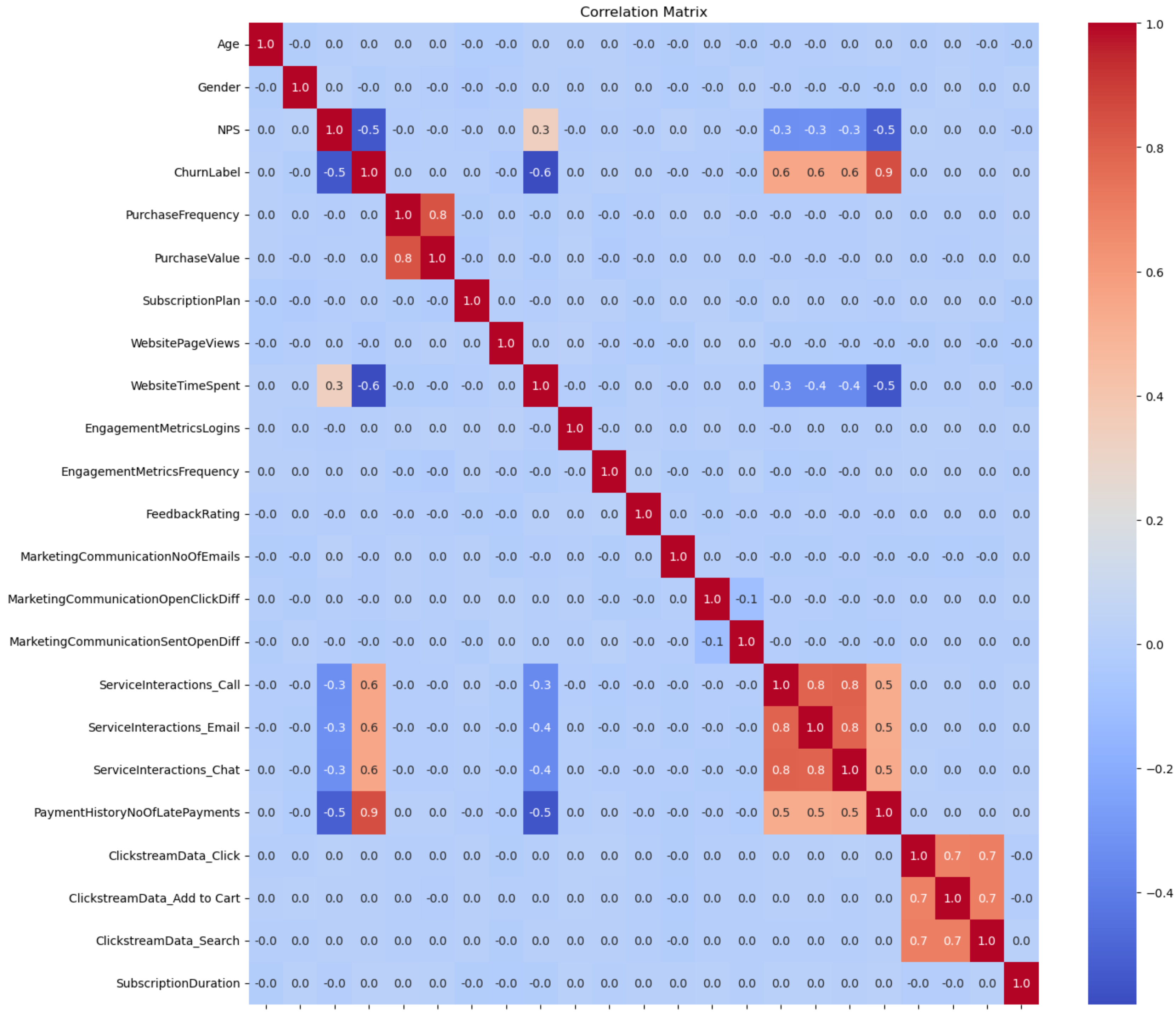
Enconding The String Parameters

In [21]:
```
# Gender encoding
gender_map = {'Male': 0, 'Female': 1}

# Apply the encoding map for Gender and replace NaN values with a specific encoding (e.g., 0)
df_['Gender'] = df_['Gender'].map(gender_map)

# Replace NaN values with a default value, e.g., 0 (or another value if preferred)
df_['Gender'] = df_['Gender'].fillna(0).astype(int)  # Converting to integer if needed

# SubscriptionPlan encoding
unique_subscription_plans = df_['SubscriptionPlan'].unique()
subscription_plan_map = {unique_subscription_plans[i]: i for i in range(len(unique_subscription_plans))}

# EngagementMetricsFrequency encoding
unique_engagement_frequency = df_['EngagementMetricsFrequency'].unique()
engagement_frequency_map = {unique_engagement_frequency[i]: i for i in range(len(unique_engagement_frequency)

# Encode the SubscriptionPlan and EngagementMetricsFrequency columns
df_['SubscriptionPlan'] = df_['SubscriptionPlan'].map(subscription_plan_map)
df_['EngagementMetricsFrequency'] = df_['EngagementMetricsFrequency'].map(engagement_frequency_map)
```

In [22]:
```
df.loc[0]
```

Out[22]:
```
Age                                    31.00
Gender                                  0.00
NPS                                     3.00
ChurnLabel                              1.00
PurchaseFrequency                      38.00
PurchaseValue                        3994.72
SubscriptionPlan                        0.00
WebsitePageViews                       49.00
WebsiteTimeSpent                       15.00
EngagementMetricsLogins                19.00
EngagementMetricsFrequency              0.00
FeedbackRating                          1.00
MarketingCommunicationNoOfEmails        8.00
MarketingCommunicationOpenClickDiff   319.00
MarketingCommunicationSentOpenDiff    818.00
ServiceInteractions_Call                1.00
ServiceInteractions_Email               1.00
ServiceInteractions_Chat                2.00
PaymentHistoryNoOfLatePayments         40.00
ClickstreamData_Click                   4.00
ClickstreamData_Add to Cart             8.00
ClickstreamData_Search                 12.00
SubscriptionDuration                  871.00
Name: 0, dtype: float64
```

In [23]:
```
df_corr = df_.corr()

# Plot the correlation matrix
plt.figure(figsize=(15, 15))
sns.heatmap(df_corr, annot=True, cmap='coolwarm', fmt='.1f')
plt.title('Correlation Matrix')
plt.show()
```


Correlation Matrix
Age
Gender
NPS
ChurnLabel
PurchaseFrequency
PurchaseValue
SubscriptionPlan
WebsitePageViews
WebsiteTimeSpent
EngagementMetricsLogins
EngagementMetricsFrequency
FeedbackRating
MarketingCommunicationNoOfEmails
MarketingCommunicationOpenClickDiff
MarketingCommunicationSentOpenDiff
ServiceInteractions_Call
ServiceInteractions_Email
ServiceInteractions_Chat
PaymentHistoryNoOfLatePayments
ClickstreamData_Click
ClickstreamData_Add to Cart
ClickstreamData_Search
SubscriptionDuration

Split dta into train, test and validation sets

In [24]:
```
import pandas as pd
from sklearn.model_selection import train_test_split

# Define feature and target variables
X = df_.drop(columns=['ChurnLabel'])
y = df_['ChurnLabel']

# First split: Training set (80%) and Other set (20%)
X_train, X_other, y_train, y_other = train_test_split(
    X, y, train_size=0.8, random_state=42
)

# Second split: Split the Other set into Test set (70% of the 20%) and Validation set (30% of the 20%)
X_test, X_val, y_test, y_val = train_test_split(
    X_other, y_other, test_size=0.3, random_state=42
)

# Print shapes to verify
print(f"Training set: {X_train.shape}, Validation set: {X_val.shape}, Test set: {X_test.shape}")
```

```
Training set: (9986, 22), Validation set: (750, 22), Test set: (1747, 22)
```

In [25]:
```
ss = StandardScaler()
X_train = ss.fit_transform(X_train)
X_val = ss.transform(X_val)
X_test = ss.transform(X_test)
```

Modelling

Two different models for modelling:

- LogisticRegression
- DecisisonTreeClassifier

Metrics:

- Accuracy Score,
- Precision Score,
- Recall Score,
- F1 Score,

In [26]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

def evaluate(X, y, model, subset=''):
    y_pred = model.predict(X)

    # Calculate metrics
    accuracy = accuracy_score(y, y_pred)
    precision = precision_score(y, y_pred)
    recall = recall_score(y, y_pred)
    f1 = f1_score(y, y_pred)

    # Print the evaluation metrics
    print(f'{subset} Accuracy Score: {accuracy:.4f}')
    print(f'{subset} Precision Score: {precision:.4f}')
    print(f'{subset} Recall Score: {recall:.4f}')
    print(f'{subset} F1 Score: {f1:.4f}')
```

Modelling with Logistic Regression

In [27]:
```
# Build the model
lr = LogisticRegression()
lr.fit(X_train, y_train)

# Evaluate the model on train and the validation subsets
evaluate(X_train, y_train, lr, 'Train')
evaluate(X_val, y_val, lr, 'Validation')
```

```
Train Accuracy Score: 0.9710
Train Precision Score: 0.9767
Train Recall Score: 0.9659
Train F1 Score: 0.9713
Validation Accuracy Score: 0.9680
Validation Precision Score: 0.9644
Validation Recall Score: 0.9697
Validation F1 Score: 0.9670
```

Modelling with Decision Trees

In [28]:
```
# Build the model
dt = DecisionTreeClassifier(max_depth=5)
dt.fit(X_train, y_train)

#Evaluate on train and validation subsets
evaluate(X_train, y_train, dt, subset='Train')
evaluate(X_val, y_val, dt, subset='Validation')
```

```
Train Accuracy Score: 0.9769
Train Precision Score: 0.9775
Train Recall Score: 0.9770
Train F1 Score: 0.9773
Validation Accuracy Score: 0.9667
Validation Precision Score: 0.9617
Validation Recall Score: 0.9697
Validation F1 Score: 0.9657
```

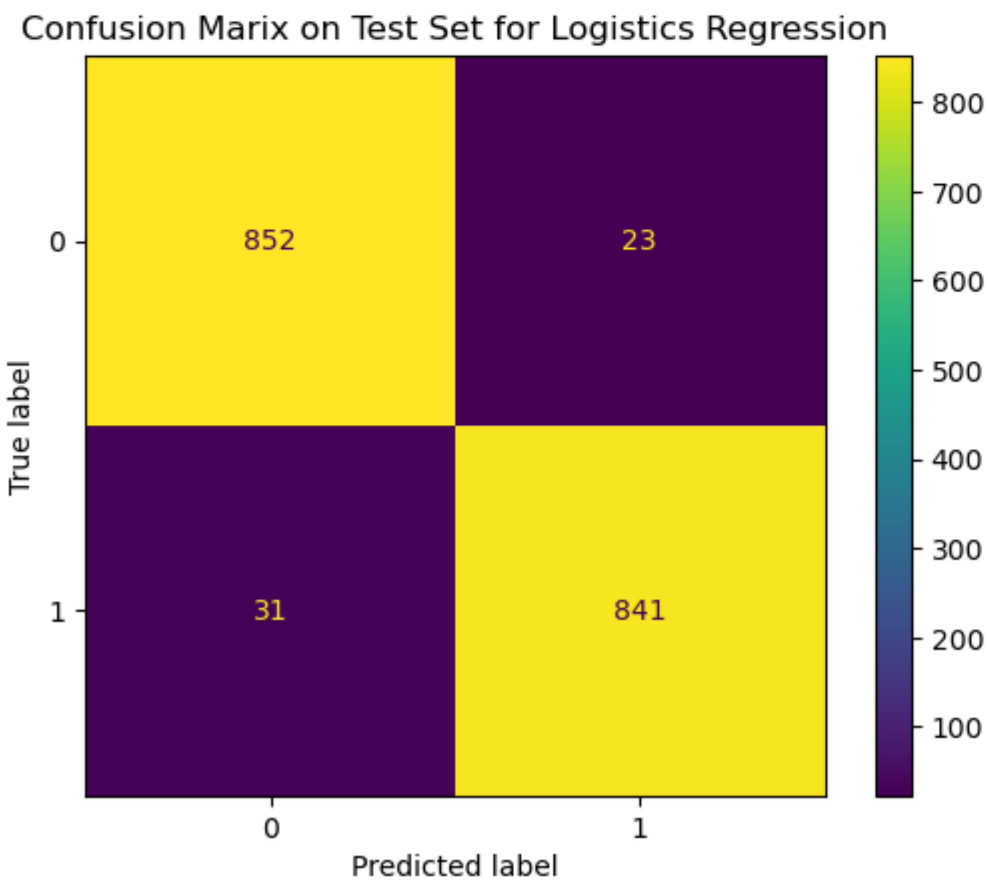
Evaluation on the Test Set

In [29]:
```
evaluate(X_test, y_test, lr, 'LogisticRegression Test')
evaluate(X_test, y_test, dt, 'DecisionTreeClassifier Test')
```

```
LogisticRegression Test Accuracy Score: 0.9691
LogisticRegression Test Precision Score: 0.9734
LogisticRegression Test Recall Score: 0.9644
LogisticRegression Test F1 Score: 0.9689
DecisionTreeClassifier Test Accuracy Score: 0.9731
DecisionTreeClassifier Test Precision Score: 0.9736
DecisionTreeClassifier Test Recall Score: 0.9725
DecisionTreeClassifier Test F1 Score: 0.9730
```

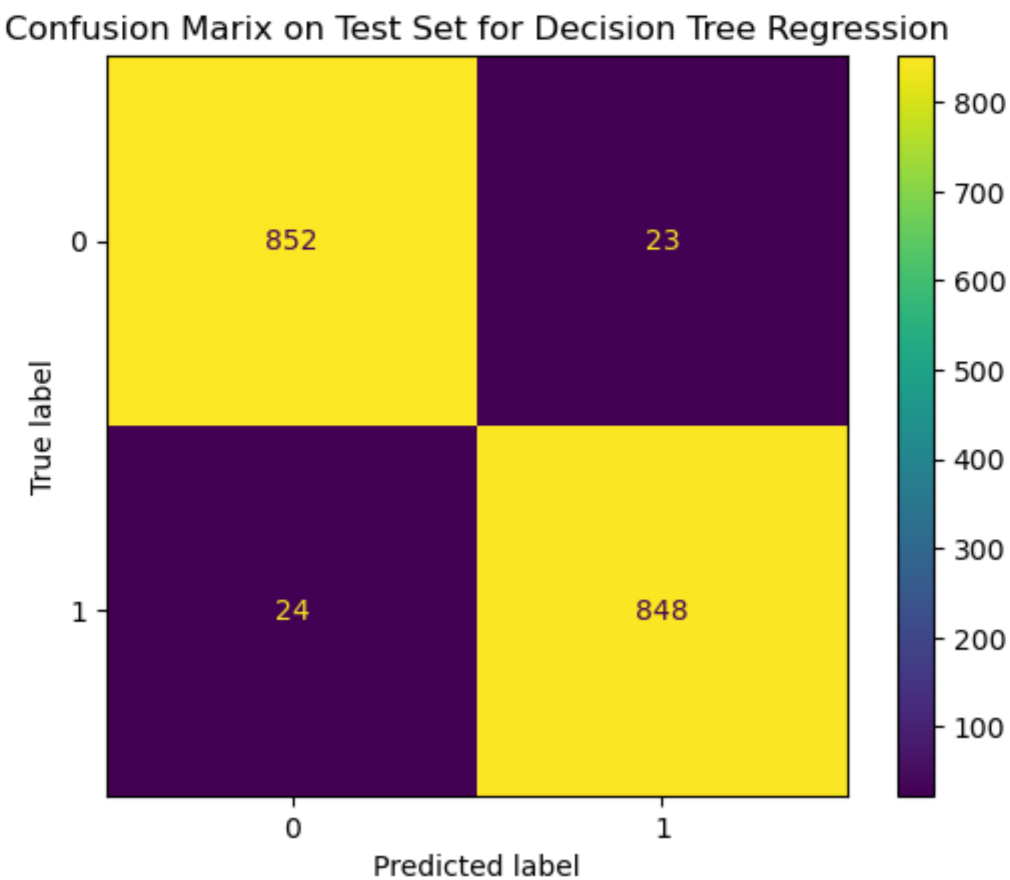
In [30]:
```
# Predictions for Logistic Regression on test set
lr_y_pred = lr.predict(X_test)
logistic_regression_confusion_matrix = confusion_matrix(y_test, lr_y_pred)

display = ConfusionMatrixDisplay(confusion_matrix=logistic_regression_confusion_matrix)
display.plot()
plt.title('Confusion Marix on Test Set for Logistics Regression')
plt.show
```

Out[30]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [31]:
```python
# Predictions for Logistic Regression on test set
dt_y_pred = dt.predict(X_test)
decision_tree_confusion_matrix = confusion_matrix(y_test, dt_y_pred)

display = ConfusionMatrixDisplay(confusion_matrix=decision_tree_confusion_matrix)
display.plot()
plt.title('Confusion Marix on Test Set for Decision Tree Regression')
plt.show
```

Out[31]: <function matplotlib.pyplot.show(close=None, block=None)>



Conclusion

The Most Important features:

- The number of service interactions the customer has had through call, Email, and Chat
- The number of times the customer has made late payments,
- The time spent on the company's website,
- The Net Promoter Score (NPS)

In [ ]:

```

```