In [1]:
```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import numpy as np
warnings.filterwarnings('ignore')

df= pd.read_csv('data.csv',encoding='unicode_escape')
df['Payment_Method'] = np.random.choice(['Credit Card', 'Debit Card', 'Cash', 'Apple Pay'], size=len(df))
df
```

Out[1]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Payment_Method
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom	Credit Card
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom	Cash
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom	Credit Card
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom	Apple Pay
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom	Credit Card
...	...	...	...	...	...	...	...	...	...
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	12/9/2011 12:50	0.85	12680.0	France	Apple Pay
541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	12/9/2011 12:50	2.10	12680.0	France	Cash
541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	12/9/2011 12:50	4.15	12680.0	France	Debit Card
541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	12/9/2011 12:50	4.15	12680.0	France	Apple Pay
541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	12/9/2011 12:50	4.95	12680.0	France	Credit Card

541909 rows × 9 columns

Tasks

1. Data Processing:

In [2]:
```python
df.describe().T
```

Out[2]:

	count	mean	std	min	25%	50%	75%	max
Quantity	541909.0	9.552250	218.081158	-80995.00	1.00	3.00	10.00	80995.0
UnitPrice	541909.0	4.611114	96.759853	-11062.06	1.25	2.08	4.13	38970.0
CustomerID	406829.0	15287.690570	1713.600303	12346.00	13953.00	15152.00	16791.00	18287.0

In [3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 9 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   InvoiceNo       541909 non-null  object 
 1   StockCode       541909 non-null  object 
 2   Description     540455 non-null  object 
 3   Quantity        541909 non-null  int64  
 4   InvoiceDate     541909 non-null  object 
 5   UnitPrice       541909 non-null  float64
 6   CustomerID      406829 non-null  float64
 7   Country         541909 non-null  object 
 8   Payment_Method  541909 non-null  object 
dtypes: float64(2), int64(1), object(6)
memory usage: 37.2+ MB
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
InvoiceNo              0
StockCode              0
Description         1454
Quantity               0
InvoiceDate            0
UnitPrice              0
CustomerID        135080
Country                0
Payment_Method         0
dtype: int64
```

In [5]:
```
df.dropna(inplace=True)
df
```

Out[5]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Payment_Method
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom	Credit Card
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom	Cash
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom	Credit Card
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom	Apple Pay
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom	Credit Card
...	...	...	...	...	...	...	...	...	...
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	12/9/2011 12:50	0.85	12680.0	France	Apple Pay
541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	12/9/2011 12:50	2.10	12680.0	France	Cash
541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	12/9/2011 12:50	4.15	12680.0	France	Debit Card
541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	12/9/2011 12:50	4.15	12680.0	France	Apple Pay
541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	12/9/2011 12:50	4.95	12680.0	France	Credit Card

406829 rows × 9 columns

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
InvoiceNo         0
StockCode         0
Description       0
Quantity          0
InvoiceDate       0
UnitPrice         0
CustomerID        0
Country           0
Payment_Method    0
dtype: int64
```

In [7]:
```python
import numpy as np

df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
df['CustomerID'] = df['CustomerID'].apply(np.int64)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 406829 entries, 0 to 541908
Data columns (total 9 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   InvoiceNo       406829 non-null  object
 1   StockCode       406829 non-null  object
 2   Description     406829 non-null  object
 3   Quantity        406829 non-null  int64
 4   InvoiceDate     406829 non-null  datetime64[ns]
 5   UnitPrice       406829 non-null  float64
 6   CustomerID      406829 non-null  int64
 7   Country         406829 non-null  object
 8   Payment_Method  406829 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(2), object(5)
memory usage: 31.0+ MB
```

In [8]:
```python
df = df.drop_duplicates()
df
```

Out[8]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Payment_Method
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850	United Kingdom	Credit Card
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850	United Kingdom	Cash
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850	United Kingdom	Credit Card
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850	United Kingdom	Apple Pay
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850	United Kingdom	Credit Card
...	...	...	...	...	...	...	...	...	...
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	12680	France	Apple Pay
541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	12680	France	Cash
541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	12680	France	Debit Card
541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	12680	France	Apple Pay
541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	12680	France	Credit Card

405430 rows × 9 columns

2. RFM Calculations:

In [9]:
```
# Recent purchase date
# InvoiceDay to datetime
df_copy = df.copy()
df_copy['InvoiceDay'] = df_copy['InvoiceDate'].dt.date
rfm = df_copy.groupby('CustomerID')['InvoiceDay'].max().reset_index()
rfm['InvoiceDay'] = pd.to_datetime(rfm['InvoiceDay'])

# Extract day
most_recent_date = rfm['InvoiceDay'].max()

# days since the last purchase
rfm['Days_Since_Last_Purchase'] = (most_recent_date - rfm['InvoiceDay']).dt.days

# Remove InvoiceDay column
rfm = rfm.drop(columns=['InvoiceDay'])

# Total  transactions
total_transactions = df_copy.groupby('CustomerID')['InvoiceNo'].nunique().reset_index()
total_transactions.rename(columns={'InvoiceNo': 'Total_Transactions'}, inplace=True)

# Total products
total_products_purchased = df_copy.groupby('CustomerID')['Quantity'].sum().reset_index()
total_products_purchased.rename(columns={'Quantity': 'Total_Products_Purchased'}, inplace=True)

# Merge
rfm = pd.merge(rfm, total_products_purchased, on='CustomerID', how='left')
rfm = pd.merge(rfm, total_transactions, on='CustomerID')

rfm
```

Out[9]:

	CustomerID	Days_Since_Last_Purchase	Total_Products_Purchased	Total_Transactions
0	12346	325	0	2
1	12347	2	2458	7
2	12348	75	2341	4
3	12349	18	631	1
4	12350	310	197	1
...	...	...	...	...
4367	18280	277	45	1
4368	18281	180	54	1
4369	18282	7	98	3
4370	18283	3	1378	16
4371	18287	42	1586	3

4372 rows × 4 columns

In [10]:
```
# Calculate the total spend by each customer
df['Total_Spend'] = df['UnitPrice'] * df['Quantity']
total_spend = df.groupby('CustomerID')['Total_Spend'].sum().reset_index()
```

```python
# Calculate the total number of transactions made by each customer
total_transactions = df.groupby('CustomerID')['InvoiceNo'].nunique().reset_index()
total_transactions.rename(columns={'InvoiceNo': 'Total_Transactions'}, inplace=True)

# Calculate the average transaction value for each customer
average_transaction_value = total_spend.merge(total_transactions, on='CustomerID')
average_transaction_value['Average_Transaction_Value'] = average_transaction_value['Total_Spend'] / average_transaction_value['Total_Transactions']

# Merge the new features into the rfm dataframe
rfm = pd.merge(rfm, total_spend, on='CustomerID')
rfm = pd.merge(rfm, average_transaction_value[['CustomerID', 'Average_Transaction_Value']], on='CustomerID')

rfm
```

Out[10]:

	CustomerID	Days_Since_Last_Purchase	Total_Products_Purchased	Total_Transactions	Total_Spend	Average_Transaction_Value
0	12346	325	0	2	0.00	0.000000
1	12347	2	2458	7	4310.00	615.714286
2	12348	75	2341	4	1797.24	449.310000
3	12349	18	631	1	1757.55	1757.550000
4	12350	310	197	1	334.40	334.400000
...	...	...	...	...	...	...
4367	18280	277	45	1	180.60	180.600000
4368	18281	180	54	1	80.82	80.820000
4369	18282	7	98	3	176.60	58.866667
4370	18283	3	1378	16	2074.22	129.638750
4371	18287	42	1586	3	1837.28	612.426667

4372 rows × 6 columns

3. RFM Segmentation:

In [11]:

```python
#  most recent purchase date
most_recent_date = df.groupby('CustomerID')['InvoiceDate'].max().reset_index()

#  most recent purchase
most_recent_date['Days_Since_Last_Purchase'] = (most_recent_date['InvoiceDate'].max() - most_recent_date['InvoiceDate']).dt.days

# quartiles for Days_Since_Last_Purchase
recency_quartiles = most_recent_date['Days_Since_Last_Purchase'].quantile([0.25, 0.5, 0.75])

# Recency Scores (lower is better)
most_recent_date['Recency_Score'] = pd.qcut(most_recent_date['Days_Since_Last_Purchase'], q=4, labels=[4, 3, 2, 1])

# Frequency Scores (higher is better)
total_transactions = df.groupby('CustomerID')['InvoiceNo'].nunique().reset_index()
total_transactions.rename(columns={'InvoiceNo': 'Total_Transactions'}, inplace=True)
most_recent_date = most_recent_date.merge(total_transactions, on='CustomerID')

most_recent_date['Frequency_Rank'] = most_recent_date['Total_Transactions'].rank(method='first')
most_recent_date['Frequency_Score'] = pd.qcut(most_recent_date['Frequency_Rank'], q=4, labels=[1, 2, 3, 4])

# Monetary Scores (higher is better)
```

```python
total_spend = df.groupby('CustomerID')['Total_Spend'].sum().reset_index()
most_recent_date = most_recent_date.merge(total_spend, on='CustomerID')
most_recent_date['Monetary_Score'] = pd.qcut(most_recent_date['Total_Spend'], q=4, labels=[1, 2, 3, 4])

# Create the RFM Score
most_recent_date['RFM_Score'] = most_recent_date['Recency_Score'].astype(str) + most_recent_date['Frequency_Score'].astype(str) + most_recent_date['Monetary_Score'].astype(str

# Merge
rfm = pd.merge(rfm, most_recent_date[['CustomerID', 'Recency_Score', 'Frequency_Score', 'Monetary_Score', 'RFM_Score']], on='CustomerID', how='left')

rfm
```

Out[11]:

	CustomerID	Days_Since_Last_Purchase	Total_Products_Purchased	Total_Transactions	Total_Spend	Average_Transaction_Value	Recency_Score	Frequency_Score	Monetary_Score	RFM_Score
0	12346	325	0	2	0.00	0.000000	1	2	1	121
1	12347	2	2458	7	4310.00	615.714286	4	4	4	444
2	12348	75	2341	4	1797.24	449.310000	2	3	4	234
3	12349	18	631	1	1757.55	1757.550000	3	1	4	314
4	12350	310	197	1	334.40	334.400000	1	1	2	112
...	...	...	...	...	...	...	...	...	...	...
4367	18280	277	45	1	180.60	180.600000	1	2	1	121
4368	18281	180	54	1	80.82	80.820000	1	2	1	121
4369	18282	7	98	3	176.60	58.866667	4	3	1	431
4370	18283	3	1378	16	2074.22	129.638750	4	4	4	444
4371	18287	42	1586	3	1837.28	612.426667	3	3	4	334

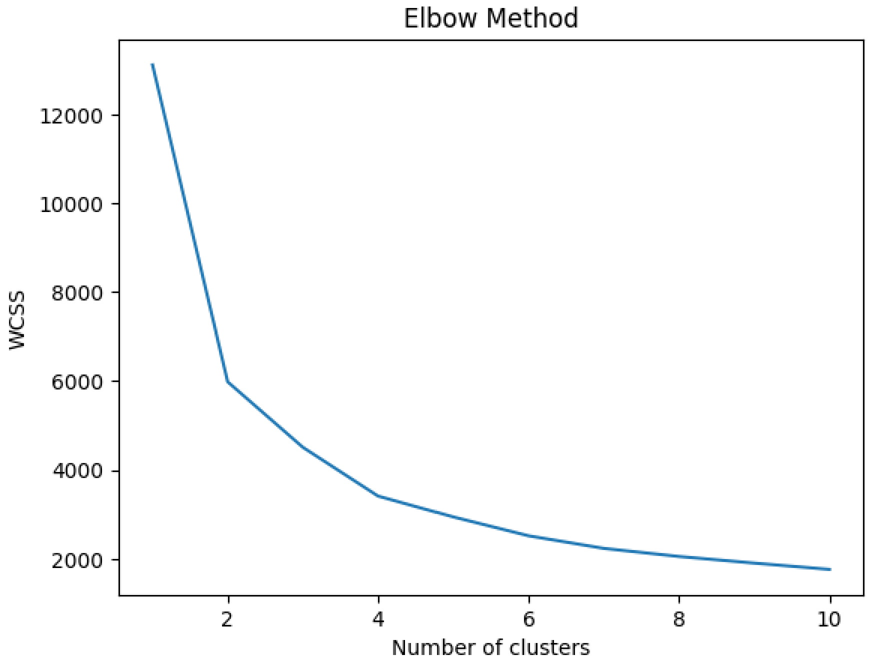
4372 rows × 10 columns

4. Customer Segmentation:

In [12]:

```python
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm[['Recency_Score', 'Frequency_Score', 'Monetary_Score']])
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
    kmeans.fit(rfm_scaled)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

k = 4

kmeans = KMeans(n_clusters=k, init='k-means++', max_iter=300, n_init=10, random_state=0)
kmeans.fit(rfm_scaled)
```

```
rfm['Cluster'] = kmeans.labels_
rfm
```



Out[12]:

	CustomerID	Days_Since_Last_Purchase	Total_Products_Purchased	Total_Transactions	Total_Spend	Average_Transaction_Value	Recency_Score	Frequency_Score	Monetary_Score	RFM_Score
0	12346	325	0	2	0.00	0.000000	1	2	1	12
1	12347	2	2458	7	4310.00	615.714286	4	4	4	444
2	12348	75	2341	4	1797.24	449.310000	2	3	4	234
3	12349	18	631	1	1757.55	1757.550000	3	1	4	314
4	12350	310	197	1	334.40	334.400000	1	1	2	112
...	...	...	...	...	...	...	...	...	...	..
4367	18280	277	45	1	180.60	180.600000	1	2	1	12
4368	18281	180	54	1	80.82	80.820000	1	2	1	12
4369	18282	7	98	3	176.60	58.866667	4	3	1	43
4370	18283	3	1378	16	2074.22	129.638750	4	4	4	444
4371	18287	42	1586	3	1837.28	612.426667	3	3	4	334

4372 rows × 11 columns

5. Segment Profiling:

In [13]:

```
print("Segment 0 Recommendations:")
print("1. Offer exclusive loyalty program to encourage purchases and increase frequency.")
print("2. Send personalized product recommendations based on searching patterns and previous purchase with special offers to tempt them back.")
print("3. Run email or SMS campaigns to keep them connected with the brand.")
print("\n")
```

```
print("Segment 1 Recommendations:")
print("1. Recognize and reward their loyalty with member points or exclusive access to new products and events.")
print("2. Suggest complementary products to increase their order value.")
print("3. Ask for their feedback on products purchased and services to further tailor your offerings.")
print("\n")

print("Segment 2 Recommendations:")
print("1. Recommend higher-value products or bundles to increase their spend.")
print("2. Create promotions for limited-time offers to pull them to make more frequent purchases.")
print("3. Share content that shows the benefits of your products to boost their value.")
print("\n")

print("Segment 3 Recommendations:")
print("1. Send targeted campaigns with attracting offers.")
print("2. Identify the reasons for their non-purchase and develop strategies to win them back.")
print("3. Ask for feedback and work on improving the aspects that pushed them away from purchasing.")
print("\n")
```

```
Segment 0 Recommendations:
1. Offer exclusive loyalty program to encourage purchases and increase frequency.
2. Send personalized product recommendations based on searching patterns and previous purchase with special offers to tempt them back.
3. Run email or SMS campaigns to keep them connected with the brand.


Segment 1 Recommendations:
1. Recognize and reward their loyalty with member points or exclusive access to new products and events.
2. Suggest complementary products to increase their order value.
3. Ask for their feedback on products purchased and services to further tailor your offerings.


Segment 2 Recommendations:
1. Recommend higher-value products or bundles to increase their spend.
2. Create promotions for limited-time offers to pull them to make more frequent purchases.
3. Share content that shows the benefits of your products to boost their value.


Segment 3 Recommendations:
1. Send targeted campaigns with attracting offers.
2. Identify the reasons for their non-purchase and develop strategies to win them back.
3. Ask for feedback and work on improving the aspects that pushed them away from purchasing.
```

6. Marketing Recommendations:

In [14]:

```
# marketing recommendations for each customer segment
marketing_recommendations = {
    'High-Value Customers': {
        'Retention': 'Focus on retaining these customers through loyalty programs and exclusive offers.',
        'Upsell': 'Identify complementary products and offer bundle deals to increase sales.',
    },
    'Potential High-Value Customers': {
        'Promotions': 'Offer incentives to encourage additional purchases and discounts on related products.',
        'Personalization': 'Use purchase history for personalized product recommendations.',
    },
    'Low-Frequency, High-Value Customers': {
        'Win-Back Campaigns': 'Target inactive customers with special promotions to reactivate them.',
        'Subscription Models': 'Introduce subscription services to ensure steady revenue.',
    },
    'Low-Value Customers': {
```

```
        'Customer Education': 'Provide informative content to help customers understand product value.',
        'Reactivation Campaigns': 'Create reactivation campaigns with exclusive offers.',
    }
}

# recommendations based on customer cluster
def get_recommendations(cluster):
    if cluster in marketing_recommendations:
        return marketing_recommendations[cluster]
    else:
        return {'General Recommendations': 'Collect customer feedback and conduct A/B testing for optimization.'}

# Apply recommendations
rfm['Marketing_Recommendations'] = rfm['Cluster'].apply(get_recommendations)

rfm[['CustomerID', 'Cluster', 'Marketing_Recommendations']]
```

Out[14]:

	CustomerID	Cluster	Marketing_Recommendations
0	12346	3	{'General Recommendations': 'Collect customer ...
1	12347	2	{'General Recommendations': 'Collect customer ...
2	12348	0	{'General Recommendations': 'Collect customer ...
3	12349	1	{'General Recommendations': 'Collect customer ...
4	12350	3	{'General Recommendations': 'Collect customer ...
...	...	...	...
4367	18280	3	{'General Recommendations': 'Collect customer ...
4368	18281	3	{'General Recommendations': 'Collect customer ...
4369	18282	1	{'General Recommendations': 'Collect customer ...
4370	18283	2	{'General Recommendations': 'Collect customer ...
4371	18287	2	{'General Recommendations': 'Collect customer ...

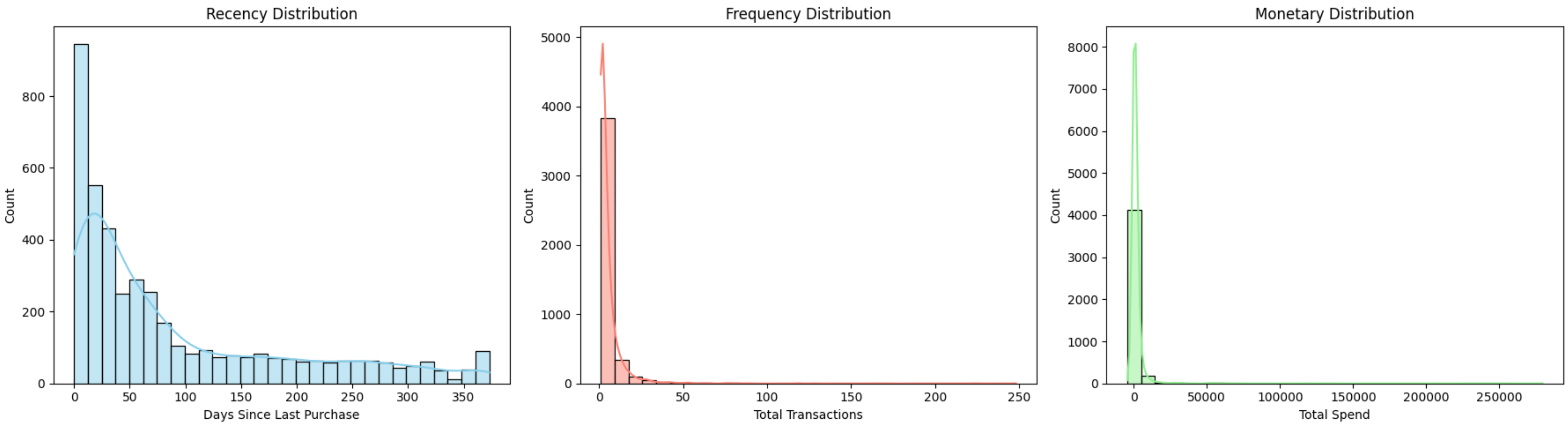
4372 rows × 3 columns

7. Visualization:

In [15]:

```
plt.figure(figsize=(18, 5))

# Recency distribution
plt.subplot(131)
sns.histplot(rfm['Days_Since_Last_Purchase'], bins=30, kde=True, color='skyblue')
plt.title('Recency Distribution')
plt.xlabel('Days Since Last Purchase')

# Frequency distribution
plt.subplot(132)
sns.histplot(rfm['Total_Transactions'], bins=30, kde=True, color='salmon')
plt.title('Frequency Distribution')
plt.xlabel('Total Transactions')

# Monetary distribution
plt.subplot(133)
sns.histplot(rfm['Total_Spend'], bins=30, kde=True, color='lightgreen')
plt.title('Monetary Distribution')
```

```
plt.xlabel('Total Spend')

plt.tight_layout()
plt.show()

# Group customers by their assigned clusters
cs = rfm.groupby('Cluster').agg({
    'Days_Since_Last_Purchase': 'mean',
    'Total_Products_Purchased': 'mean',
    'Total_Transactions': 'mean',
    'Total_Spend': 'mean',
    'Average_Transaction_Value': 'mean',
    'CustomerID': 'count'
}).reset_index()

# Rename columns for clarity
cs = cs.rename(columns={
    'Days_Since_Last_Purchase': 'Average_Recency',
    'Total_Products_Purchased': 'Average_Products_Purchased',
    'Total_Transactions': 'Average_Transactions',
    'Total_Spend': 'Average_Spend',
    'Average_Transaction_Value': 'Average_Transaction_Value',
    'CustomerID': 'Customer_Count'
})

cs
```



Out[15]:

	Cluster	Average_Recency	Average_Products_Purchased	Average_Transactions	Average_Spend	Average_Transaction_Value	Customer_Count
0	0	120.704370	907.957584	4.465296	1499.140221	417.984138	778
1	1	23.017073	288.419512	1.953659	428.840341	257.131054	820
2	2	15.993502	2677.876534	10.992780	4600.750889	368.010828	1385
3	3	191.115911	180.976962	1.359971	290.608849	240.298499	1389

Find the solutions to these questions:

1. Data Overview

In [16]:
```
# Size of the dataset
num_rows, num_columns = df.shape
print(f"Size of the dataset: {num_rows} rows and {num_columns} columns")
print("\n")

# Description of each column
column_descriptions = df.describe(include='all')
print("Column Descriptions:")
print(column_descriptions)
print("\n")

# Time period covered by the dataset
start_date = df['InvoiceDate'].min()
end_date = df['InvoiceDate'].max()
print(f"Time period covered by the dataset: From {start_date} to {end_date}")
```

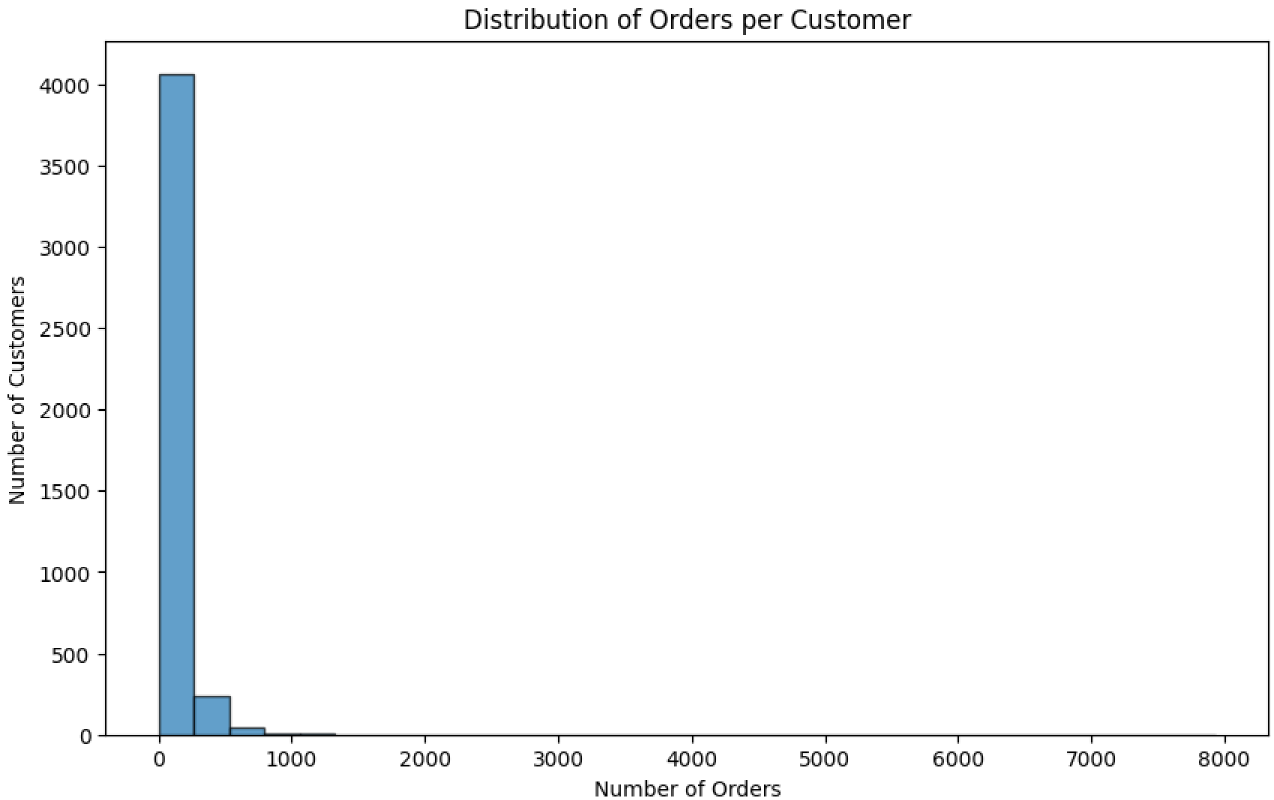
```
Size of the dataset: 405430 rows and 10 columns


Column Descriptions:
       InvoiceNo StockCode                          Description       Quantity  \
count     405430    405430                               405430  405430.000000   
unique     22190      3684                                 3896            NaN   
top       576339    85123A   WHITE HANGING HEART T-LIGHT HOLDER            NaN   
freq         542      2072                                 2065            NaN   
mean         NaN       NaN                                  NaN      12.093656   
min          NaN       NaN                                  NaN  -80995.000000   
25%          NaN       NaN                                  NaN       2.000000   
50%          NaN       NaN                                  NaN       5.000000   
75%          NaN       NaN                                  NaN      12.000000   
max          NaN       NaN                                  NaN   80995.000000   
std          NaN       NaN                                  NaN     249.121269   

                          InvoiceDate      UnitPrice     CustomerID  \
count                          405430  405430.000000  405430.000000   
unique                            NaN            NaN            NaN   
top                               NaN            NaN            NaN   
freq                              NaN            NaN            NaN   
mean    2011-07-10 15:32:52.091211776       3.463937   15285.791907   
min               2010-12-01 08:26:00       0.000000   12346.000000   
25%               2011-04-06 15:02:00       1.250000   13951.000000   
50%               2011-07-31 11:45:00       1.950000   15150.000000   
75%               2011-10-20 12:43:00       3.750000   16791.000000   
max               2011-12-09 12:50:00   38970.000000   18287.000000   
std                               NaN      69.434488    1713.730034   

               Country Payment_Method    Total_Spend  
count           405430         405430  405430.000000  
unique              37              4            NaN  
top     United Kingdom    Credit Card            NaN  
freq            360504         101445            NaN  
mean               NaN            NaN      20.456493  
min                NaN            NaN -168469.600000  
25%                NaN            NaN       4.200000  
50%                NaN            NaN      11.250000  
75%                NaN            NaN      19.500000  
max                NaN            NaN  168469.600000  
std                NaN            NaN     428.327593  


Time period covered by the dataset: From 2010-12-01 08:26:00 to 2011-12-09 12:50:00
```

2. Customer Analysis

In [17]:
```python
# Unique Customers
unique_customers = df['CustomerID'].nunique()
print(f"Number of unique customers: {unique_customers}")

# Distribution of the number of orders per customer
orders_per_customer = df['CustomerID'].value_counts()
print("Distribution of orders per customer:")
print(orders_per_customer)

plt.figure(figsize=(10, 6))
plt.hist(orders_per_customer, bins=30, edgecolor='k', alpha=0.7)
plt.title('Distribution of Orders per Customer')
plt.xlabel('Number of Orders')
```

```python
plt.ylabel('Number of Customers')
plt.show()

# Top 5 customers with the most purchases by order count
top_customers = orders_per_customer.head(5)
print("Top 5 customers with the most purchases by order count:")
print(top_customers)
```

```
Number of unique customers: 4372
Distribution of orders per customer:
CustomerID
17841    7935
14911    5902
14096    5128
12748    4603
14606    2775
         ...
17331       1
13391       1
18113       1
17715       1
17846       1
Name: count, Length: 4372, dtype: int64
```



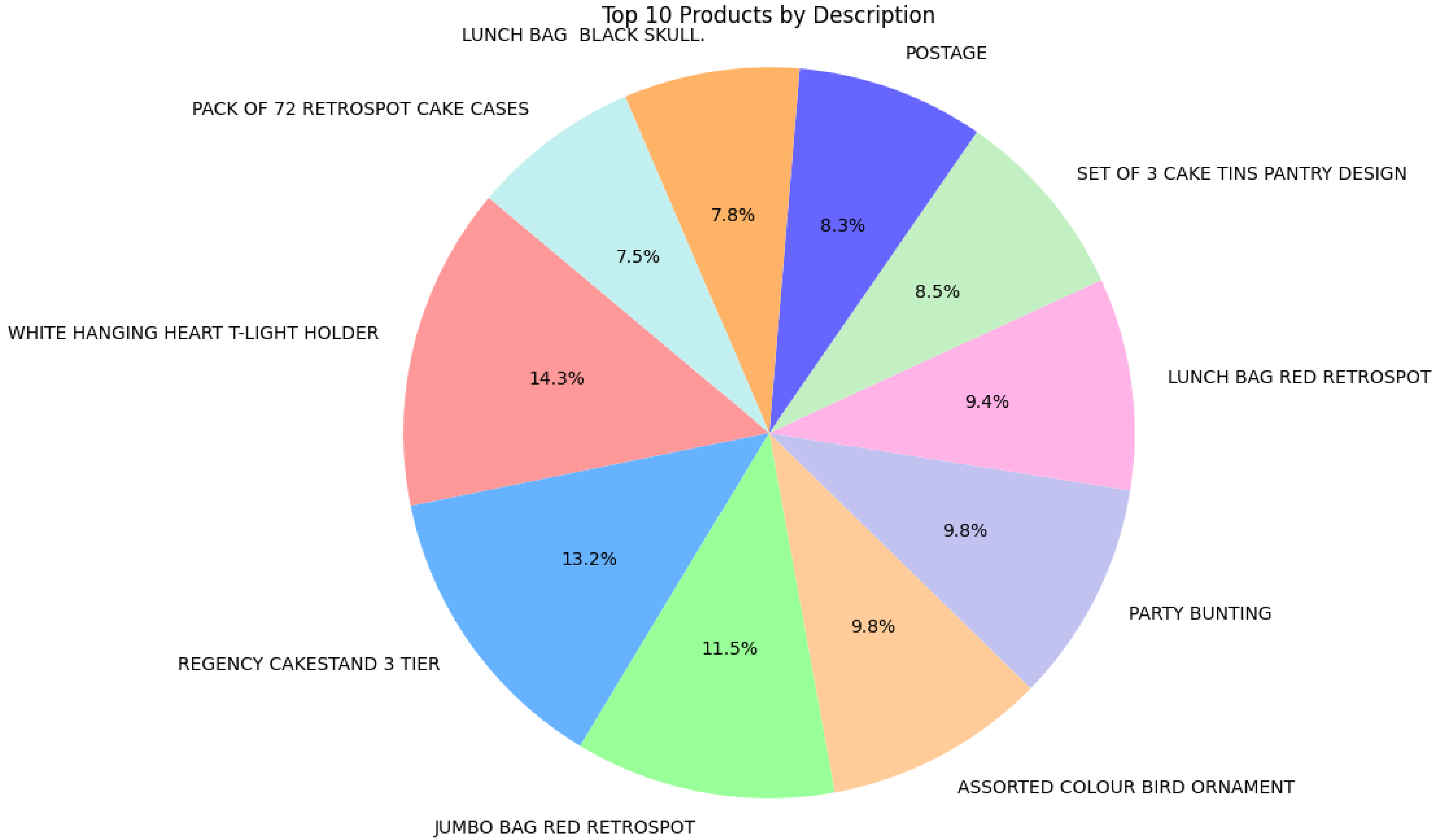
```
Top 5 customers with the most purchases by order count:
CustomerID
17841    7935
14911    5902
14096    5128
12748    4603
14606    2775
Name: count, dtype: int64
```

3. Product Analysis

In [18]:

```python
# top 10 most frequently purchased products
df['Total_Spend'] = df['UnitPrice']*df['Quantity']

product_counts = df['Description'].value_counts()
top_10_products = product_counts.head(10)
print(top_10_products)
print("\n")
product_quantity = df.groupby('Description')['Quantity'].sum()

plt.figure(figsize=(8, 8))
custom_colors = ['#FF9999', '#66B2FF', '#99FF99', '#FFCC99', '#c2c2f0', '#ffb3e6', '#c2f0c2', '#6666ff', '#ffb366', '#c2f0f0']
plt.pie(top_10_products, labels=top_10_products.index, autopct='%1.1f%%', startangle=140, colors=custom_colors)
plt.axis('equal')
plt.title('Top 10 Products by Description')

plt.show()

# average price of products
average_price = df['UnitPrice'].mean()
print("Average Price of Products:", average_price)
print("\n")

# the total revenue for each category
product_revenue = df.groupby('Description')['Total_Spend'].sum()
highest_revenue_stock = product_revenue.idxmax()
highest_revenue = product_revenue.max()
print("StockCode with the Highest Revenue:", highest_revenue_stock)
print("Total Revenue:", highest_revenue)
print("\n")
```

```
Description
WHITE HANGING HEART T-LIGHT HOLDER    2065
REGENCY CAKESTAND 3 TIER              1900
JUMBO BAG RED RETROSPOT               1661
ASSORTED COLOUR BIRD ORNAMENT         1415
PARTY BUNTING                         1414
LUNCH BAG RED RETROSPOT               1352
SET OF 3 CAKE TINS PANTRY DESIGN      1230
POSTAGE                               1196
LUNCH BAG  BLACK SKULL.               1120
PACK OF 72 RETROSPOT CAKE CASES       1076
Name: count, dtype: int64
```

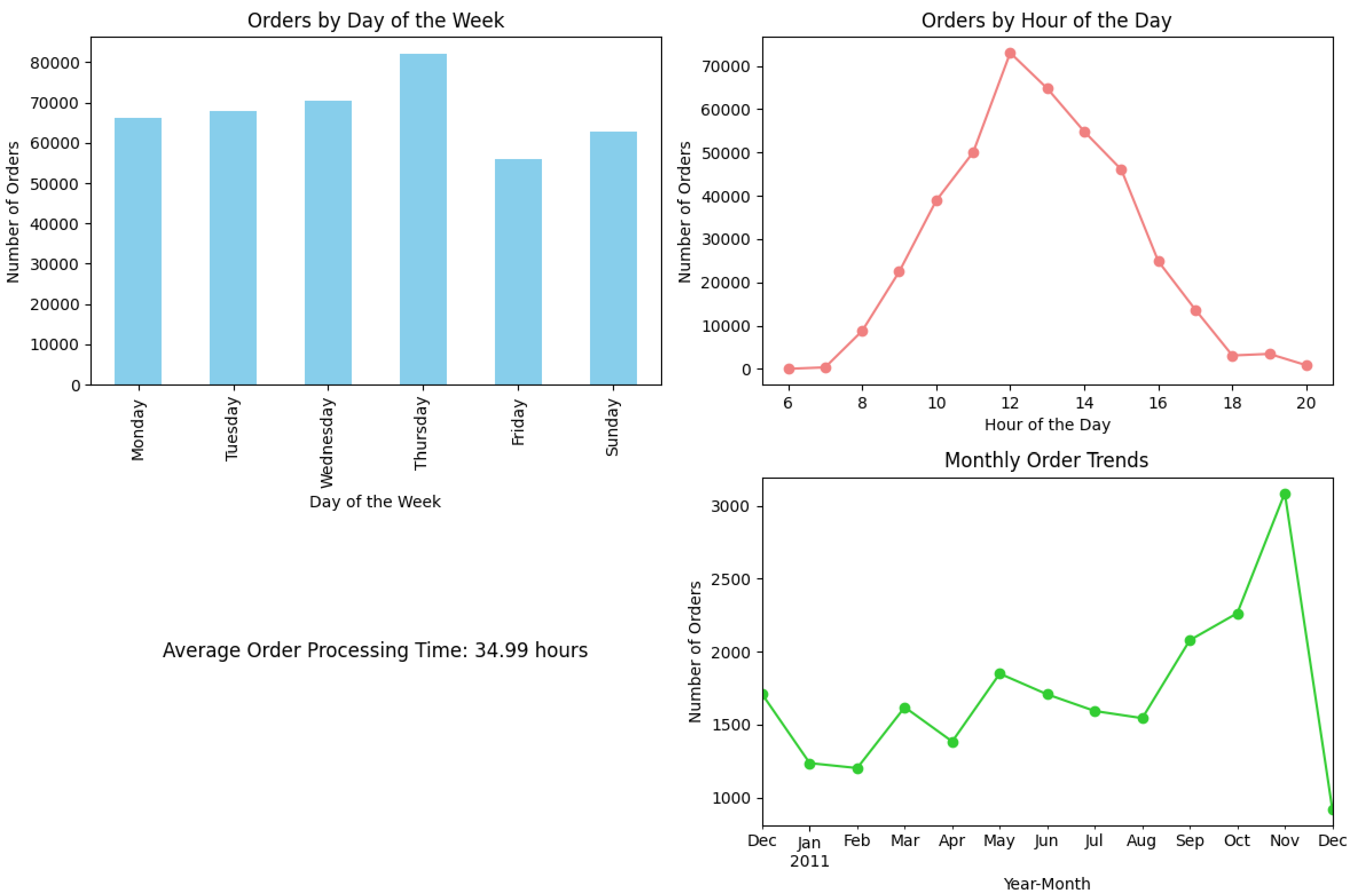



```
Average Price of Products: 3.4639370396862597


StockCode with the Highest Revenue: REGENCY CAKESTAND 3 TIER
Total Revenue: 132806.65
```

4. Time Analysis

In [19]:
```
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
df['OrderDay'] = df['InvoiceDate'].dt.date
df['OrderTime'] = df['InvoiceDate'].dt.time
df['OrderHour'] = df['InvoiceDate'].dt.hour
df['DayOfWeek'] = df['InvoiceDate'].dt.dayofweek

orders_by_day_of_week = df['DayOfWeek'].value_counts().sort_index()
orders_by_hour = df['OrderHour'].value_counts().sort_index()

# Average order processing time
df['OrderProcessTime'] = (df['InvoiceDate'] - df.groupby('CustomerID')['InvoiceDate'].shift(1)).dt.total_seconds() / 3600
average_process_time = df['OrderProcessTime'].mean()
```

```
#seasonal trends (monthly) in the dataset
df['YearMonth'] = df['InvoiceDate'].dt.to_period('M')
monthly_order_count = df.groupby('YearMonth')['InvoiceNo'].nunique()

plt.figure(figsize=(12, 8))

#day of the week with the most orders
plt.subplot(221)
orders_by_day_of_week.plot(kind='bar', color='skyblue')
plt.title('Orders by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Number of Orders')

# hour of the day with the most orders
plt.subplot(222)
orders_by_hour.plot(kind='line', marker='o', color='lightcoral')
plt.title('Orders by Hour of the Day')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Orders')

# Display the average order processing time
plt.subplot(223)
plt.text(0.5, 0.5, f'Average Order Processing Time: {average_process_time:.2f} hours',
         fontsize=12, ha='center', va='center', transform=plt.gca().transAxes)
plt.axis('off')

# Plot seasonal trends (monthly)
plt.subplot(224)
monthly_order_count.plot(kind='line', marker='o', color='limegreen')
plt.title('Monthly Order Trends')
plt.xlabel('Year-Month')
plt.ylabel('Number of Orders')

plt.tight_layout()


day_mapping = {
    0: 'Monday',
    1: 'Tuesday',
    2: 'Wednesday',
    3: 'Thursday',
    4: 'Friday',
    5: 'Saturday',
    6: 'Sunday'
}

orders_by_day_of_week.index = orders_by_day_of_week.index.map(day_mapping)
plt.subplot(221)
orders_by_day_of_week.plot(kind='bar', color='skyblue')
plt.title('Orders by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Number of Orders')
plt.show()
```

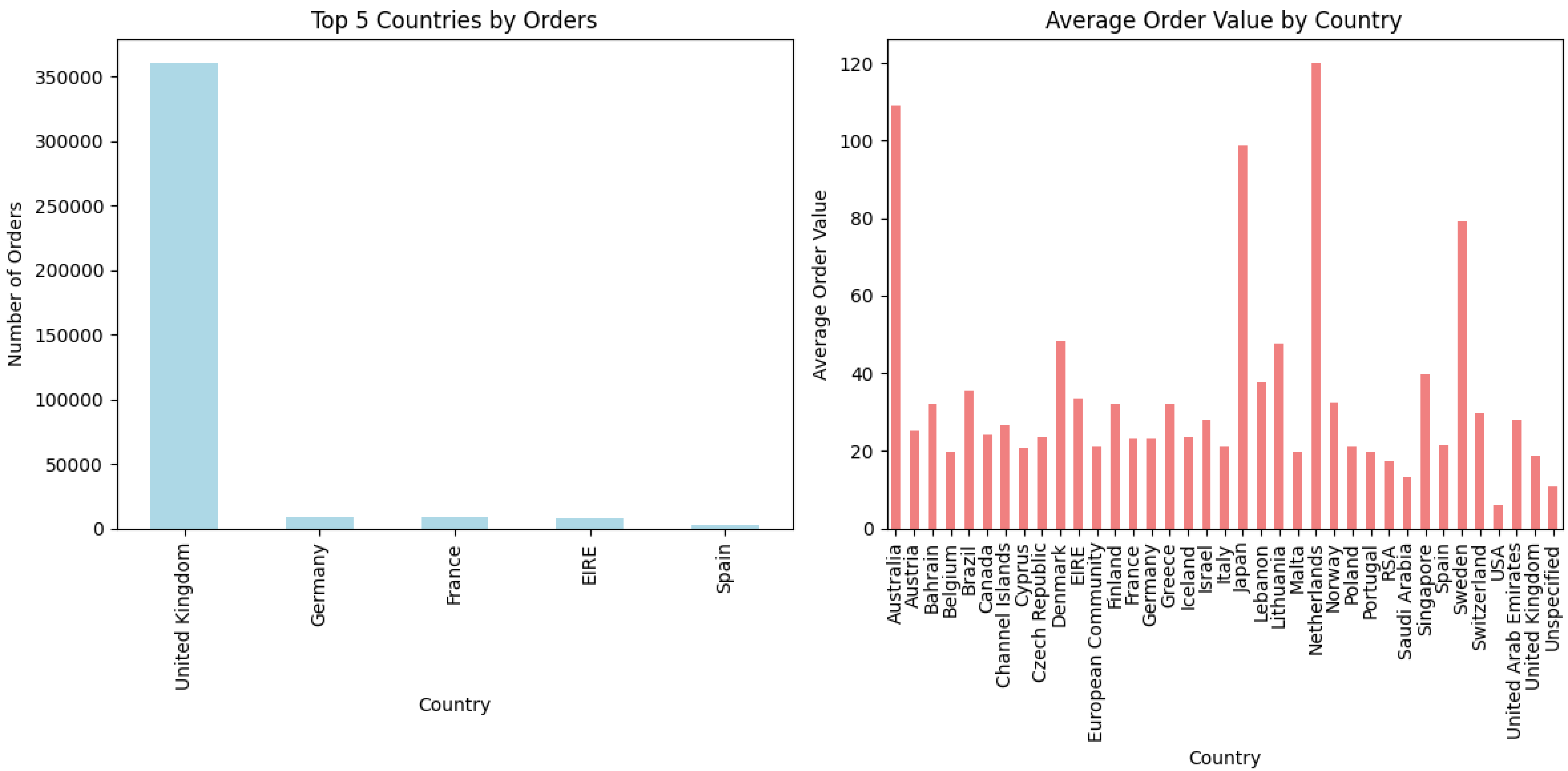


5.Geographical Analysis

In [20]:

```
import pandas as pd
import matplotlib.pyplot as plt

oc = df['Country'].value_counts()
avgc = df.groupby('Country')['Total_Spend'].mean()
t5 = oc.head(5)

correlation = avgc.corr(df['Country'])

plt.figure(figsize=(12, 6))
```

```python
plt.subplot(121)
t5.plot(kind='bar', color='lightblue')
plt.title('Top 5 Countries by Orders')
plt.xlabel('Country')
plt.ylabel('Number of Orders')

plt.subplot(122)
avgc.plot(kind='bar', color='lightcoral')
plt.title('Average Order Value by Country')
plt.xlabel('Country')
plt.ylabel('Average Order Value')

plt.tight_layout()
plt.show()

print(f'Correlation between Country and Average Order Value:\n{correlation}')
```




```
Correlation between Country and Average Order Value:
nan
```

6. Payment Analysis

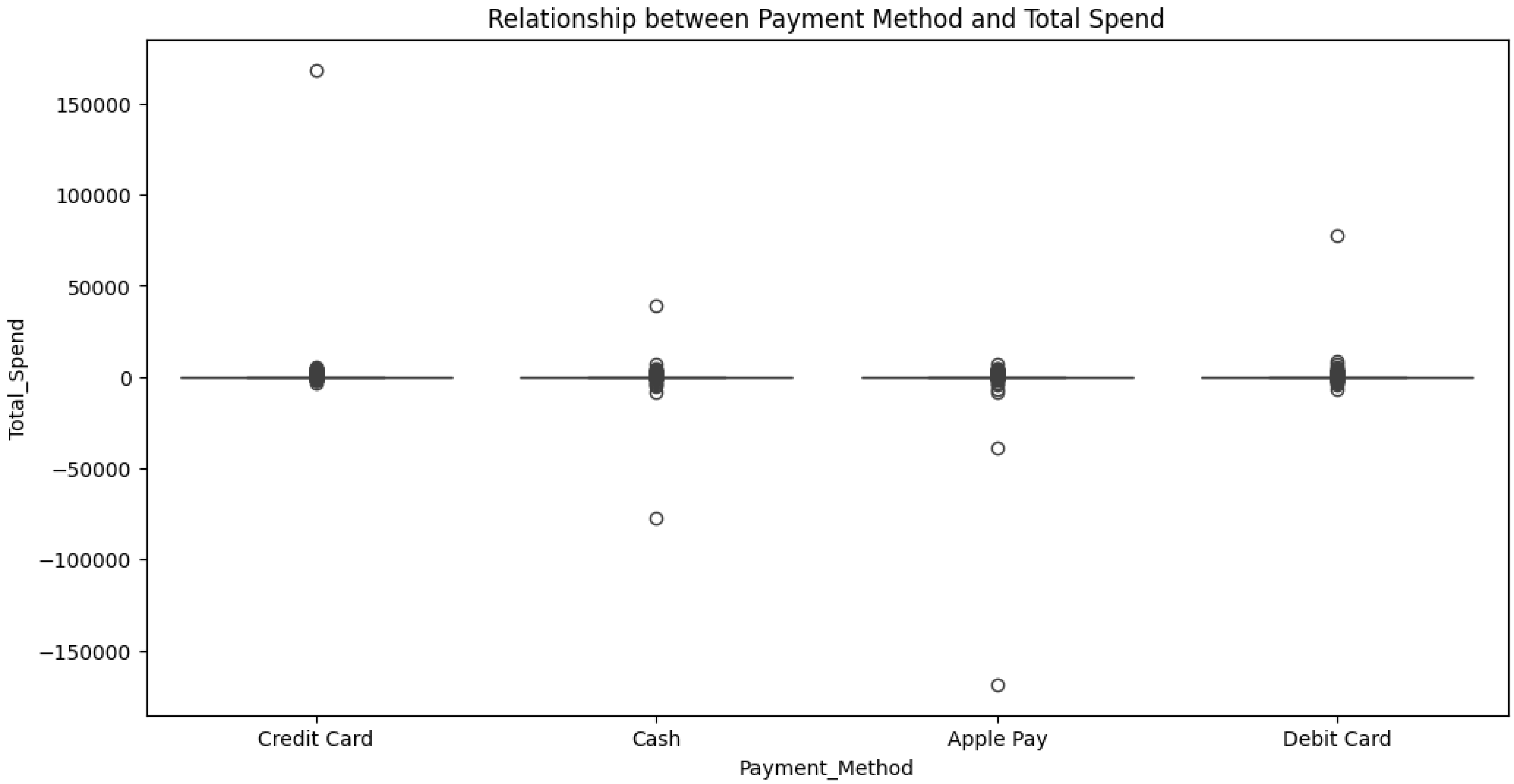
In [21]:

```python
payment_method_counts = df['Payment_Method'].value_counts()

# Display the most common payment methods
```

```
print("Most Common Payment Methods:")
print(payment_method_counts)
```

```
Most Common Payment Methods:
Payment_Method
Credit Card    101445
Apple Pay      101441
Debit Card     101283
Cash           101261
Name: count, dtype: int64
```

In [22]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
sns.boxplot(x='Payment_Method', y='Total_Spend', data=df)
plt.title('Relationship between Payment Method and Total Spend')
plt.show()
```



7. Customer Behavior

In [23]:
```
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
customer_activity = df.groupby('CustomerID')['InvoiceDate'].agg(['min', 'max'])

#average duration of customer activity
customer_activity['ActivityDuration'] = (customer_activity['max'] - customer_activity['min']).dt.days.mean()

print(f'Average Duration of Customer Activity: {customer_activity["ActivityDuration"].mean()} days')
```

```
#recency and frequency
recency = (customer_activity['max'].max() - customer_activity['max']).dt.days
frequency = df['CustomerID'].value_counts()
customer_segments = pd.DataFrame({'Recency': recency, 'Frequency': frequency})

# segment thresholds
recency_threshold = customer_segments['Recency'].median()
frequency_threshold = customer_segments['Frequency'].median()

# Assign segments
customer_segments['Segment'] = 'Low Activity'
customer_segments.loc[(customer_segments['Recency'] <= recency_threshold) & (customer_segments['Frequency'] > frequency_threshold), 'Segment'] = 'High Activity'

print('Customer Segments:')
print(customer_segments)
```

```
Average Duration of Customer Activity: 133.38586459286367 days
Customer Segments:
            Recency  Frequency        Segment
CustomerID
12346           325          2   Low Activity
12347             1        182  High Activity
12348            74         31   Low Activity
12349            18         73  High Activity
12350           309         17   Low Activity
...             ...        ...            ...
18280           277         10   Low Activity
18281           180          7   Low Activity
18282             7         13   Low Activity
18283             3        742  High Activity
18287            42         70  High Activity

[4372 rows x 3 columns]
```

8. Returns and Refunds

In [24]:
```
returns = df[df['Quantity'] < 0]

# percentage of returns or refunds
total_orders = len(df)
orr = len(returns)
pr = (orr / total_orders) * 100

print(f'Percentage of Orders with Returns or Refunds: {pr:.2f}%')
# Group the returns by product category
rc = returns.groupby('Description')['InvoiceNo'].count()
toc = df.groupby('Description')['InvoiceNo'].count()

# percentage of returns for each category
prc = (rc / toc) * 100

print('Percentage of Returns by Product Category:')
print(prc)
```

```
Percentage of Orders with Returns or Refunds: 2.19%
Percentage of Returns by Product Category:
Description
 4 PURPLE FLOCK DINNER CANDLES           NaN
 50'S CHRISTMAS GIFT BAG LARGE      0.909091
 DOLLY GIRL BEAKER                  1.438849
 I LOVE LONDON MINI BACKPACK             NaN
 I LOVE LONDON MINI RUCKSACK             NaN
                                      ...
ZINC T-LIGHT HOLDER STARS SMALL     1.244813
ZINC TOP  2 DOOR WOODEN SHELF      18.181818
ZINC WILLIE WINKIE  CANDLE STICK    0.518135
ZINC WIRE KITCHEN ORGANISER              NaN
ZINC WIRE SWEETHEART LETTER TRAY         NaN
Name: InvoiceNo, Length: 3896, dtype: float64
```

9. Profitability Analysis

In [25]:
```
# df['TR'] = df['Quantity'] * (df['UnitPrice'])
total_profit = df['Total_Spend'].sum()

print("Total Profit Generated: ${:.2f}".format(total_profit))

df['Revenue'] = (df['Quantity'] * df['UnitPrice'])

top_5_products_profit_margin = df[['StockCode', 'Description', 'Revenue']].sort_values(by='Revenue', ascending=False).head(5)

print("\nTop 5 Products with the Highest Revenue:")
print(top_5_products_profit_margin)
```

```
Total Profit Generated: $8293675.84

Top 5 Products with the Highest Revenue:
       StockCode                          Description    Revenue
540421     23843          PAPER CRAFT , LITTLE BIRDIE  168469.60
61619      23166       MEDIUM CERAMIC TOP STORAGE JAR   77183.60
222680     22502       PICNIC BASKET WICKER 60 PIECES   38970.00
173382      POST                              POSTAGE    8142.75
348325     23243  SET OF TEA COFFEE SUGAR TINS PANTRY    7144.72
```

10. Customer Satisfaction

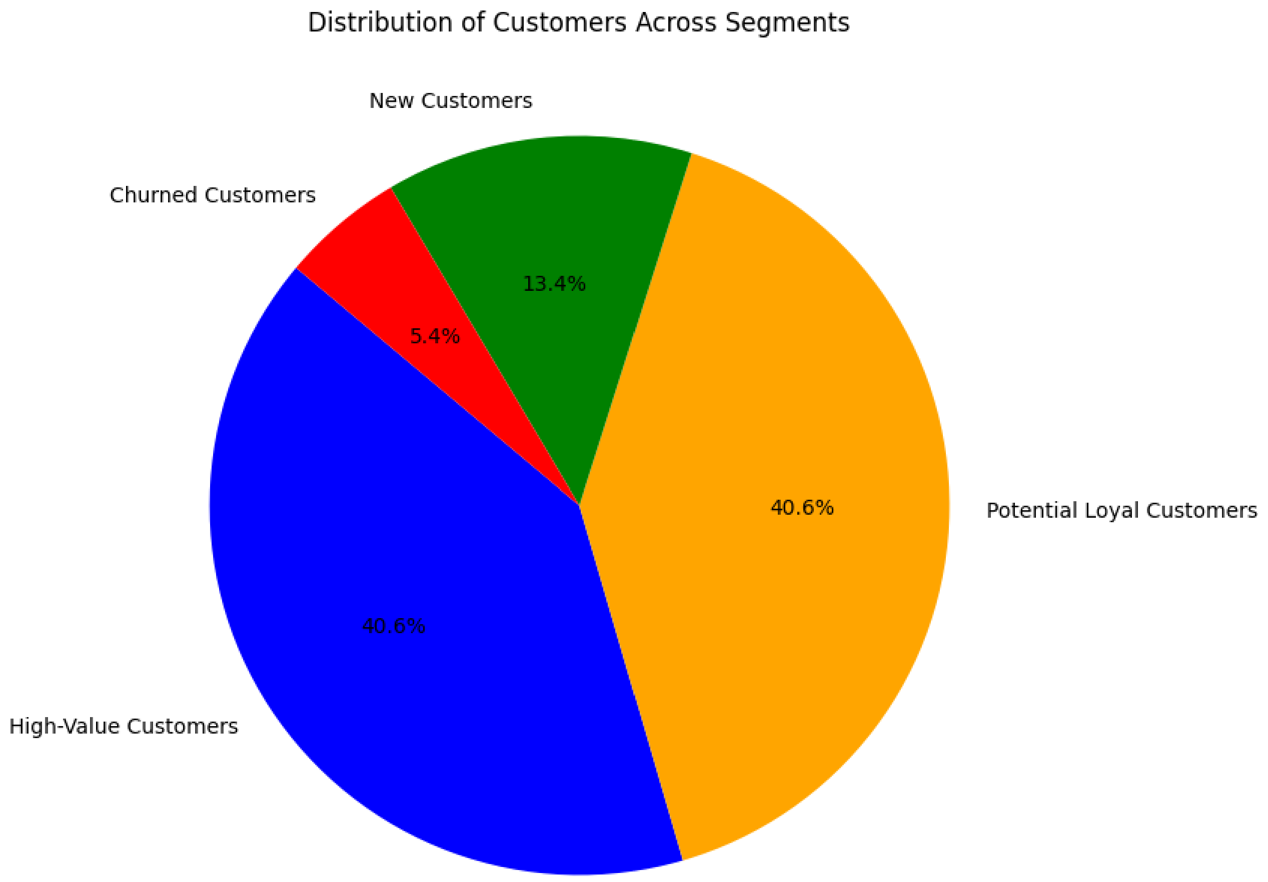
In [26]:
```
threshold_recency = 3
high_frequency_threshold = 3
moderate_monetary_threshold = 3
very_recent_threshold = 3
low_frequency_threshold = 1
low_monetary_threshold = 1
high_recency_threshold = 4

# High-Value Customers
high_value_customers = rfm[(rfm['Recency_Score'] <= threshold_recency) &
                            (rfm['Frequency_Score'] == high_frequency_threshold) &
                            (rfm['Monetary_Score'] == moderate_monetary_threshold)]

# Potential Loyal Customers
potential_loyal_customers = rfm[(rfm['Recency_Score'] <= threshold_recency) &
                                 (rfm['Frequency_Score'] == high_frequency_threshold) &
                                 (rfm['Monetary_Score'] == moderate_monetary_threshold)]
```

```python
# New Customers
new_customers = rfm[(rfm['Recency_Score'] == very_recent_threshold) &
                    (rfm['Frequency_Score'] == low_frequency_threshold) &
                    (rfm['Monetary_Score'] == low_monetary_threshold)]

# Churned Customers
churned_customers = rfm[(rfm['Recency_Score'] == high_recency_threshold) &
                        (rfm['Frequency_Score'] == low_frequency_threshold) &
                        (rfm['Monetary_Score'] == low_monetary_threshold)]

# Display the sizes of each segment
print("High-Value Customers:", len(high_value_customers))
print("Potential Loyal Customers:", len(potential_loyal_customers))
print("New Customers:", len(new_customers))
print("Churned Customers:", len(churned_customers))
```

```
High-Value Customers: 333
Potential Loyal Customers: 333
New Customers: 110
Churned Customers: 44
```

In [27]:

```python
segment_sizes = [len(high_value_customers), len(potential_loyal_customers), len(new_customers), len(churned_customers)]

# Labels for the segments
segments = ['High-Value Customers', 'Potential Loyal Customers', 'New Customers', 'Churned Customers']

# Plotting a pie chart
plt.figure(figsize=(8, 8))
plt.pie(segment_sizes, labels=segments, autopct='%1.1f%%', startangle=140, colors=['blue', 'orange', 'green', 'red'])
plt.title('Distribution of Customers Across Segments')
plt.show()
```



In [28]:
```
keywords = ['positive', 'negative', 'good', 'bad', 'like', 'dislike', 'excellent', 'poor', 'satisfied', 'unsatisfied']

positive_probabilities = [0.4, 0.1, 0.3, 0.05, 0.2, 0.05, 0.3, 0.05, 0.4, 0.1]
positive_probabilities /= np.sum(positive_probabilities)  # Normalize to ensure probabilities sum to 1

np.random.seed(42)
df['Customer_Feedback'] = np.random.choice(keywords, len(df), p=positive_probabilities)


def analyze_sentiment(keyword):
    positive_keywords = ['positive', 'good', 'like', 'excellent', 'satisfied']
    negative_keywords = ['negative', 'bad', 'dislike', 'poor', 'unsatisfied']

    if keyword in positive_keywords:
        return 'Positive'
    elif keyword in negative_keywords:
        return 'Negative'
    else:
        return 'Neutral'

df['Sentiment'] = df['Customer_Feedback'].apply(analyze_sentiment)
```

```
sentiment_counts = df['Sentiment'].value_counts()

plt.figure(figsize=(8, 5))
sentiment_counts.plot(kind='bar', color=['green', 'red', 'blue'])
plt.title('Sentiment Distribution in Customer Feedback')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.show()
```

In [ ]: