CASE STUDY

1. Data Cleaning & Preparation Assess data quality by identifying missing values, duplicates, and inconsistent data types. Ensure the data is cleaned and formatted for further analysis. This includes creating the "Month-Year" column for time-based analysis.
2. Sales Overview & Trend Analysis Provide a comprehensive overview of sales performance by calculating total Quantity and Value grouped by product category and business. Visualize these metrics and identify seasonal trends using time-series analysis.
3. Performance Analysis of Products Identify the top 5 products based on both Quantity and Value to understand which items are performing the best. This allows for strategic decisions on inventory, pricing, and marketing.
4. Customer Segmentation & Forecasting Segment businesses based on their purchase behavior and forecast future sales for the next 3 months using appropriate time-series methods (e.g., ARIMA or exponential smoothing). Use these insights to drive targeted marketing and inventory strategies.
5. Anomaly Detection & Correlation Analysis Identify any anomalous spikes or drops in sales performance and analyze the relationships between Quantity and Value to uncover key drivers of sales.
6. Strategic Insights & Operational Recommendations Provide actionable insights on Product Strategy, Customer Retention, and Operational Efficiency, leveraging the analysis to suggest ways to improve marketing, inventory, and customer engagement strategies.

In [17]:
```
#import required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

In [18]:
```
#Load the data
df = pd.read_csv('Case_study.csv')
df.head()
```

Out[18]:

	DATE	ANONYMIZED CATEGORY	ANONYMIZED PRODUCT	ANONYMIZED BUSINESS	ANONYMIZED LOCATION	QUANTITY	UNIT PRICE
0	August 18, 2024, 9:32 PM	Category-106	Product-21f4	Business-de42	Location-1ba8	1	850
1	August 18, 2024, 9:32 PM	Category-120	Product-4156	Business-de42	Location-1ba8	2	1,910
2	August 18, 2024, 9:32 PM	Category-121	Product-49bd	Business-de42	Location-1ba8	1	3,670
3	August 18, 2024, 9:32 PM	Category-76	Product-61dd	Business-de42	Location-1ba8	1	2,605
4	August 18, 2024, 9:32 PM	Category-119	Product-66e0	Business-de42	Location-1ba8	5	1,480

UNDERSTAND THE DATAFRAME STRUCTURE

In [3]:
```
#dimension of the dataframe
df.shape
```

Out[3]:
```
(333405, 7)
```

In [4]:
```
#check for column datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 333405 entries, 0 to 333404
Data columns (total 7 columns):
 #   Column               Non-Null Count   Dtype 
---  ------               --------------   ----- 
 0   DATE                 333405 non-null  object
 1   ANONYMIZED CATEGORY  333405 non-null  object
 2   ANONYMIZED PRODUCT   333405 non-null  object
 3   ANONYMIZED BUSINESS  333405 non-null  object
 4   ANONYMIZED LOCATION  333405 non-null  object
 5   QUANTITY             333405 non-null  int64 
 6   UNIT PRICE           333397 non-null  object
dtypes: int64(1), object(6)
memory usage: 17.8+ MB
```

Our dataset has 333,405 rows and 7 columns and no null values.We also observe that there is a mix of data types.

. Date: timestamp of the transaction

. Anonymized category: product category

. Anonymized product: specific product within the category

. Anonymized businnes: company or outlet selling the product

. Anonymized location: geographic location of the sale

. Quantity: number of items purchased

. Unit price: price per product.

In [19]:
```
#check for column names
df.columns
```

Out[19]:
```
Index(['DATE', 'ANONYMIZED CATEGORY', 'ANONYMIZED PRODUCT',
       'ANONYMIZED BUSINESS', 'ANONYMIZED LOCATION', 'QUANTITY', 'UNIT PRICE'],
      dtype='object')
```

In [20]:
```
#check for the missing values
df.isnull().sum()
```

Out[20]:
```
DATE                   0
ANONYMIZED CATEGORY    0
ANONYMIZED PRODUCT     0
ANONYMIZED BUSINESS    0
ANONYMIZED LOCATION    0
QUANTITY               0
UNIT PRICE             8
dtype: int64
```

In [21]:
```
# Check the rows with missing UnitPrice
missing_rows = df[df['UNIT PRICE'].isna()]
print(f"Rows with missing UnitPrice:\n{missing_rows}")
```

```
Rows with missing UnitPrice:
                              DATE ANONYMIZED CATEGORY ANONYMIZED PRODUCT  \
108112       July 3, 2024, 5:53 PM         Category-94       Product-3d7f
150961  December 16, 2024, 6:33 PM         Category-79       Product-dfc8
151142  December 22, 2024, 2:42 PM        Category-122       Product-15e0
272379     June 27, 2024, 12:15 PM         Category-92       Product-ccbc
278284    August 14, 2024, 9:09 PM        Category-101       Product-84a5
278384  December 30, 2024, 2:17 PM         Category-95       Product-15f3
310385     March 31, 2024, 2:03 PM        Category-114       Product-9204
327152    August 13, 2024, 4:20 PM        Category-107       Product-7eed

       ANONYMIZED BUSINESS ANONYMIZED LOCATION  QUANTITY UNIT PRICE
108112       Business-4fce       Location-f37d         2        NaN
150961       Business-8bbf       Location-3fc0         1        NaN
151142       Business-c575       Location-1979         3        NaN
272379       Business-14b6       Location-1979         1        NaN
278284       Business-4be1       Location-bb69        21        NaN
278384       Business-1a74       Location-f37d         1        NaN
310385       Business-c9dc       Location-689f         1        NaN
327152       Business-0d61       Location-1ba8         1        NaN
```

In [22]:
```
## Drop rows with missing UnitPrice
df= df.dropna(subset=['UNIT PRICE'])
#save the cleaned dataset
df.to_csv("cleaned_data.csv", index=False)
# Save the dropped rows to a CSV for reference
missing_rows.to_csv("dropped_rows.csv", index=False)
```

handling missing values

The UnitPrice column has 8 missing values and the original dataset had 333,405 rows. Although,these values are critical for analysis and imputation is not suitable, for accurate analysis we drop the values. After dropping 8 rows with missing values in UnitPrice, the dataset now has 333,397 rows.

In [24]:
```
#check for duplicated values
duplicate_count = df.duplicated().sum()
print(f"Total Duplicates: {duplicate_count}")
```

```
Total Duplicates: 3524
```

In [25]:
```
# a detailed view of duplicate rows
df[df.duplicated(keep=False)]
```

Out[25]:

	DATE	ANONYMIZED CATEGORY	ANONYMIZED PRODUCT	ANONYMIZED BUSINESS	ANONYMIZED LOCATION	QUANTITY	UNIT PRICE
310	May 17, 2024, 8:27 PM	Category-120	Product-1e80	Business-9909	Location-689f	1	1,970
311	May 17, 2024, 8:27 PM	Category-75	Product-8f75	Business-9909	Location-689f	1	4,020
426	January 31, 2024, 7:34 PM	Category-76	Product-e805	Business-bf85	Location-1ba8	5	7,018
526	February 5, 2024, 6:24 PM	Category-120	Product-29ee	Business-bfcd	Location-3e32	5	2,290
570	April 19, 2024, 3:19 PM	Category-75	Product-086d	Business-b48e	Location-03fc	3	2,090
...	...	...	...	...	...	...	...

Handling Duplicates

There are 5,706 duplicate rows in the dataset.

The duplicates are not errors but rather represent meaningful transactions.

This is because each row reflects distinct purchase events, occurring at the same day,time and same locations involving different quantities and unitprice for different products.

Therefore, it's prudent to retain the duplicates for the analysis:

. Each duplicate row represents a valid transaction with distinct details.

. Removing duplicates would lead to loss of information and lead to inaccurate conclusiions about total sales, trends and customer behaviour.

In [26]:
```
#renaming the columns to preferred right case
df.columns = [
    'Date',
    'Anonymized category',
    'Anonymized product',
    'Anonymized business',
    'Anonymized location',
    'Quantity',
    'UnitPrice'
]
```

In [27]:
```
# confirm the changes in column names
df.columns
```

Out[27]:
```
Index(['Date', 'Anonymized category', 'Anonymized product',
       'Anonymized business', 'Anonymized location', 'Quantity', 'UnitPrice'],
      dtype='object')
```

In [28]:
```
#Inconsistent Data Types
#Convert DATE column to datetime format.
#Remove commas and convert UNIT PRICE to float
# Add new column 'Total_Value' as a product of 'Quantity'* 'UnitPrice'

df['Date'] = pd.to_datetime(df['Date'])

df['UnitPrice'] = df['UnitPrice'].str.replace(',', '').astype(float)

df['Total_Value'] = df['Quantity'] * df['UnitPrice']
```

In [29]:
```
df.head()
```

Out[29]:

	Date	Anonymized category	Anonymized product	Anonymized business	Anonymized location	Quantity	UnitPrice	Total_Value
0	2024-08-18 21:32:00	Category-106	Product-21f4	Business-de42	Location-1ba8	1	850.0	850.0
1	2024-08-18 21:32:00	Category-120	Product-4156	Business-de42	Location-1ba8	2	1910.0	3820.0
2	2024-08-18 21:32:00	Category-121	Product-49bd	Business-de42	Location-1ba8	1	3670.0	3670.0
3	2024-08-18 21:32:00	Category-76	Product-61dd	Business-de42	Location-1ba8	1	2605.0	2605.0
4	2024-08-18 21:32:00	Category-119	Product-66e0	Business-de42	Location-1ba8	5	1480.0	7400.0

By making a copy of the dataframe, we can conduct an indepth analysis of the data's properties, gaining valuable insights that will inform subsequent analytical steps. This approach maintains the integrity of the original dataset while enabling us to perform in-depth EDA with confidence and accuracy.

In [30]:
```
#make a copy of original dataframe
df1 = df.copy()
df1.head()
```

Out[30]:

	Date	Anonymized category	Anonymized product	Anonymized business	Anonymized location	Quantity	UnitPrice	Total_Value
0	2024-08-18 21:32:00	Category-106	Product-21f4	Business-de42	Location-1ba8	1	850.0	850.0
1	2024-08-18 21:32:00	Category-120	Product-4156	Business-de42	Location-1ba8	2	1910.0	3820.0
2	2024-08-18 21:32:00	Category-121	Product-49bd	Business-de42	Location-1ba8	1	3670.0	3670.0
3	2024-08-18 21:32:00	Category-76	Product-61dd	Business-de42	Location-1ba8	1	2605.0	2605.0
4	2024-08-18 21:32:00	Category-119	Product-66e0	Business-de42	Location-1ba8	5	1480.0	7400.0

FEATURE ENGINEERING

In [31]:
```
# Create Month-Year column from datetime Date
df1['Month-Year'] = df1['Date'].dt.strftime('%B %Y')
```

In [32]:
```
# Ensure 'Month-Year' is in a recognizable datetime format
df1['Month-Year'] = pd.to_datetime(df1['Month-Year'], format='%B %Y')
# Remove the timestamp from the 'Date' column
df1['Date'] = pd.to_datetime(df1['Date']).dt.date
# Sort the dataframe by the 'Month-Year' column in chronological order
df1 = df1.sort_values(by='Month-Year')

# convert the 'Month-Year' column back to the desired string format (e.g., "January 2024")
df1['Month-Year'] = df1['Month-Year'].dt.strftime('%B %Y')

# Reset index to reflect the new order
df1 = df1.reset_index(drop=True)

# Display the sorted dataframe
print(df1.head())
```

```
         Date Anonymized category Anonymized product Anonymized business  \
0  2024-01-24         Category-76       Product-e805       Business-eb52
1  2024-01-26        Category-107       Product-8d56       Business-c89b
2  2024-01-26         Category-91       Product-cae5       Business-c89b
3  2024-01-26         Category-91       Product-e125       Business-c89b
4  2024-01-10        Category-120       Product-29ee       Business-965c

  Anonymized location  Quantity  UnitPrice  Total_Value    Month-Year
0       Location-f37d         3     7285.0      21855.0  January 2024
1       Location-03fc         1     1485.0       1485.0  January 2024
2       Location-03fc         1      615.0        615.0  January 2024
3       Location-03fc         1     1510.0       1510.0  January 2024
4       Location-3e32         5     2166.0      10830.0  January 2024
```

In [33]:
```
#a view of the first 5 rows
df1.head()
```

Out[33]:

	Date	Anonymized category	Anonymized product	Anonymized business	Anonymized location	Quantity	UnitPrice	Total_Value	Month-Year
0	2024-01-24	Category-76	Product-e805	Business-eb52	Location-f37d	3	7285.0	21855.0	January 2024
1	2024-01-26	Category-107	Product-8d56	Business-c89b	Location-03fc	1	1485.0	1485.0	January 2024
2	2024-01-26	Category-91	Product-cae5	Business-c89b	Location-03fc	1	615.0	615.0	January 2024
3	2024-01-26	Category-91	Product-e125	Business-c89b	Location-03fc	1	1510.0	1510.0	January 2024
4	2024-01-10	Category-120	Product-29ee	Business-965c	Location-3e32	5	2166.0	10830.0	January 2024

In [34]:
```
#check for data types
df1.dtypes
```

Out[34]:
```
Date                  object
Anonymized category   object
Anonymized product    object
Anonymized business   object
Anonymized location   object
Quantity               int64
UnitPrice            float64
Total_Value          float64
Month-Year            object
dtype: object
```

In [35]:
```
#statistical analysis
df1.describe()
```

Out[35]:

	Quantity	UnitPrice	Total_Value
count	333397.000000	333397.000000	3.333970e+05
mean	2.321149	2322.039538	5.369872e+03
std	3.790518	1585.256624	1.123618e+04
min	0.000000	0.000000	0.000000e+00
25%	1.000000	1420.000000	1.520000e+03
50%	1.000000	1840.000000	2.750000e+03
75%	2.000000	2755.000000	5.590000e+03
max	359.000000	16136.000000	1.914000e+06

In [36]:
```
#confirm null values
df1.isnull().sum()
```

Out[36]:
```
Date                    0
Anonymized category     0
Anonymized product      0
Anonymized business     0
Anonymized location     0
Quantity                0
UnitPrice               0
Total_Value             0
Month-Year              0
dtype: int64
```

EXPLORATORY DATA ANALYSIS

In [37]:
```
# Total Quantity and Value by Category
# Group the data by 'ANONYMIZED CATEGORY' and calculate the sum of 'Quantity' and sum 'Total_Val
sales_by_category = df1.groupby('Anonymized category').agg({
   'Quantity': 'sum',
    'Total_Value': 'sum'
}).reset_index()
```

In [38]:
```
#a view of the sales by category analysis
sales_by_category
```

Out[38]:

	Anonymized category	Quantity	Total_Value
0	Category-100	77704	136417463.0
1	Category-101	19782	35964827.0
2	Category-102	1941	501824.0
3	Category-104	1222	1564133.0
4	Category-105	1656	2844024.0
5	Category-106	6582	5986975.0
6	Category-107	2756	4211267.0
7	Category-108	9782	5159195.0
8	Category-109	1453	1269541.0
9	Category-110	10614	5583150.0
10	Category-111	6867	4495262.0
11	Category-113	752	1257258.0
12	Category-114	3	8600.0
13	Category-115	349	428430.0
14	Category-116	856	422745.0
15	Category-117	5	1550.0
16	Category-118	21	7560.0
17	Category-119	68615	103900839.0
18	Category-120	171443	322737950.0
19	Category-121	14936	22677154.0
20	Category-122	1223	3493480.0
21	Category-123	286	730730.0
22	Category-124	4	10060.0
23	Category-125	123	297060.0
24	Category-74	944	1934051.0
25	Category-75	152643	549509348.0
26	Category-76	72928	351827338.0
27	Category-77	28825	77791642.0
28	Category-78	9876	9919076.0
29	Category-79	2220	1188062.0
30	Category-81	144	72663.0
31	Category-82	4819	3980705.0
32	Category-83	2445	4058683.0
33	Category-84	12029	6852610.0
34	Category-85	23368	34298630.0
35	Category-86	8	3320.0
36	Category-89	241	138575.0
37	Category-90	15	15750.0
38	Category-91	21081	44700098.0
39	Category-92	7037	10595173.0
40	Category-94	23747	16809234.0
41	Category-95	4156	7546746.0

	Anonymized category	Quantity	Total_Value
42	Category-96	1445	2313675.0
43	Category-97	2796	2657369.0
44	Category-98	2153	2520065.0
45	Category-99	1969	1595410.0

In [39]:
```
# Group the data by 'ANONYMIZED CATEGORY' and
#calculate the sum of 'Quantity' and 'Unit price' for each category

sales_by_business = df1.groupby('Anonymized business').agg({
    # Sum the 'Quantity' column
    'Quantity': 'sum',
    # Sum the 'Value' column
    'Total_Value': 'sum'
    # # Reset the index to turn the result back into a DataFrame instead of a GroupBy object
}).reset_index()
```

In [40]:
```
#a view of the sales by businesses
sales_by_business
```

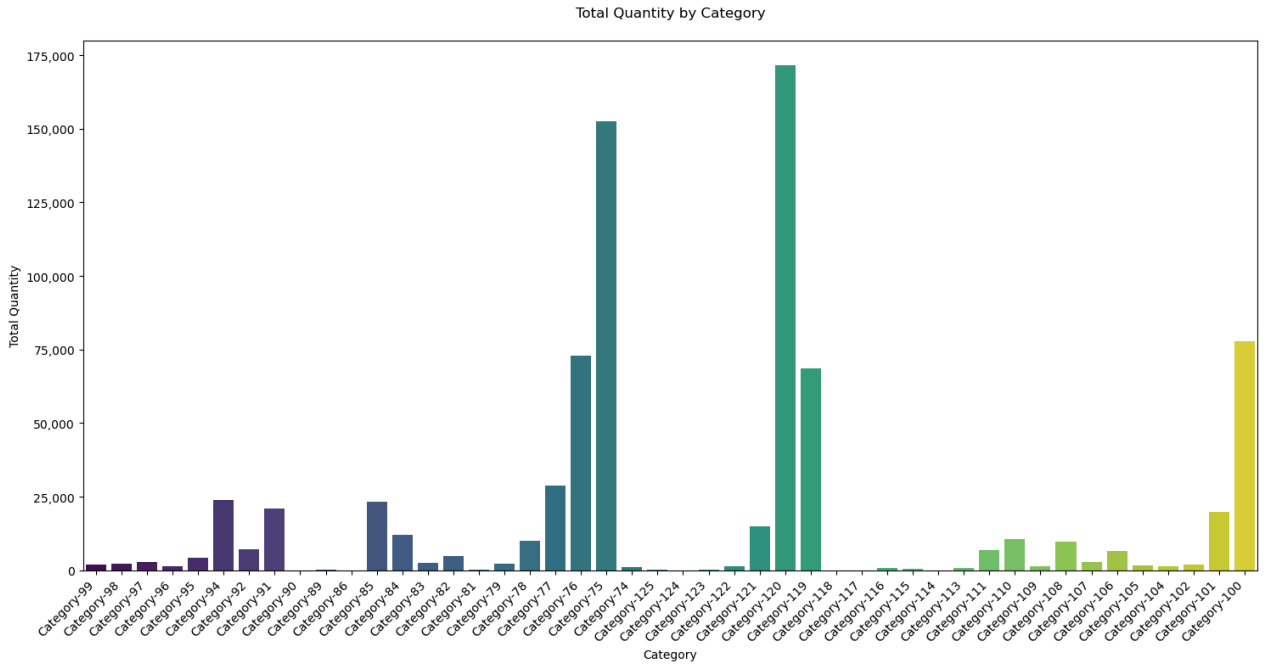
Out[40]:

	Anonymized business	Quantity	Total_Value
0	Business-0000	8	10445.0
1	Business-0005	1	2645.0
2	Business-0029	26	77340.0
3	Business-003d	98	221761.0
4	Business-0072	127	225056.0
...	...	...	...
4795	Business-ffa9	3	6740.0
4796	Business-ffae	6	10530.0
4797	Business-ffb1	266	438115.0
4798	Business-ffd2	39	78548.0
4799	Business-ffff	110	110285.0

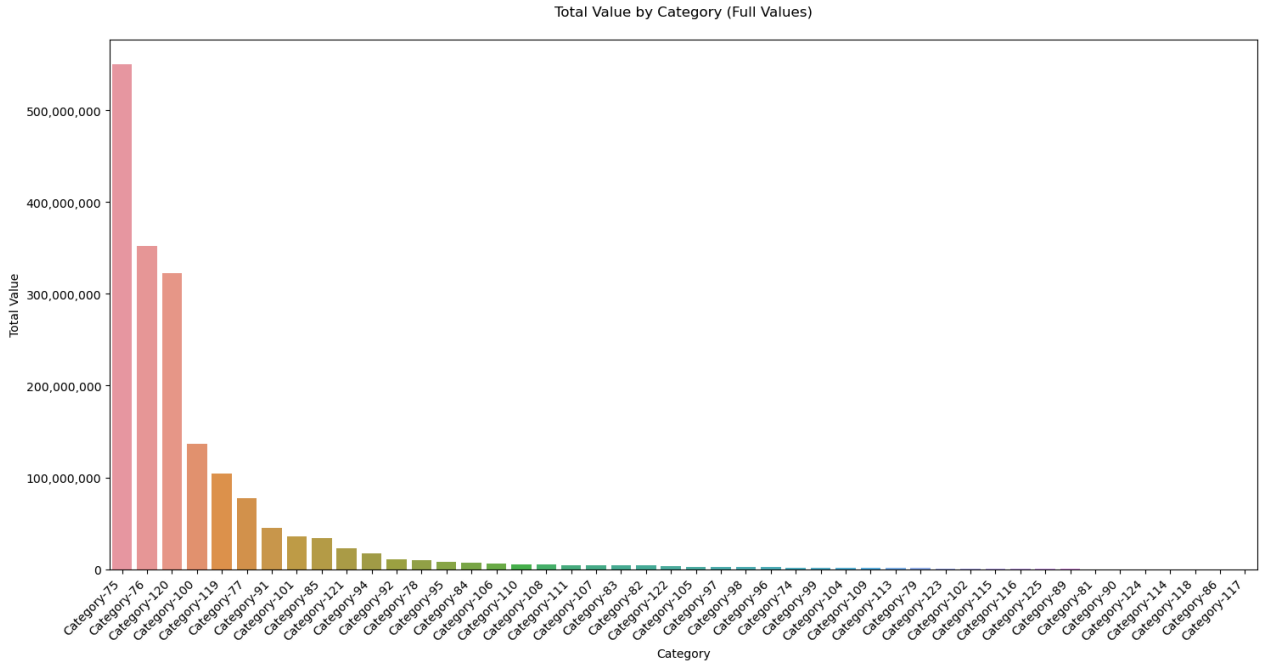
Visualization

In [44]:

```
 #Sort values in salesby category
sales_by_category_sorted = sales_by_category.sort_values('Anonymized category', ascending = Fals
# Create figure  size
plt.figure(figsize=(15, 8))

# Create barplot
sns.barplot(x='Anonymized category', y='Quantity', data=sales_by_category_sorted, palette='virid

# Rotate x-axis labels
plt.xticks(rotation=45, ha='right')

# Format y-axis labels with comma separator for thousands
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda x, p: format(int(x), ',')))

# Add title and labels
plt.title('Total Quantity by Category', pad=20)
plt.xlabel('Category')
plt.ylabel('Total Quantity')

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```

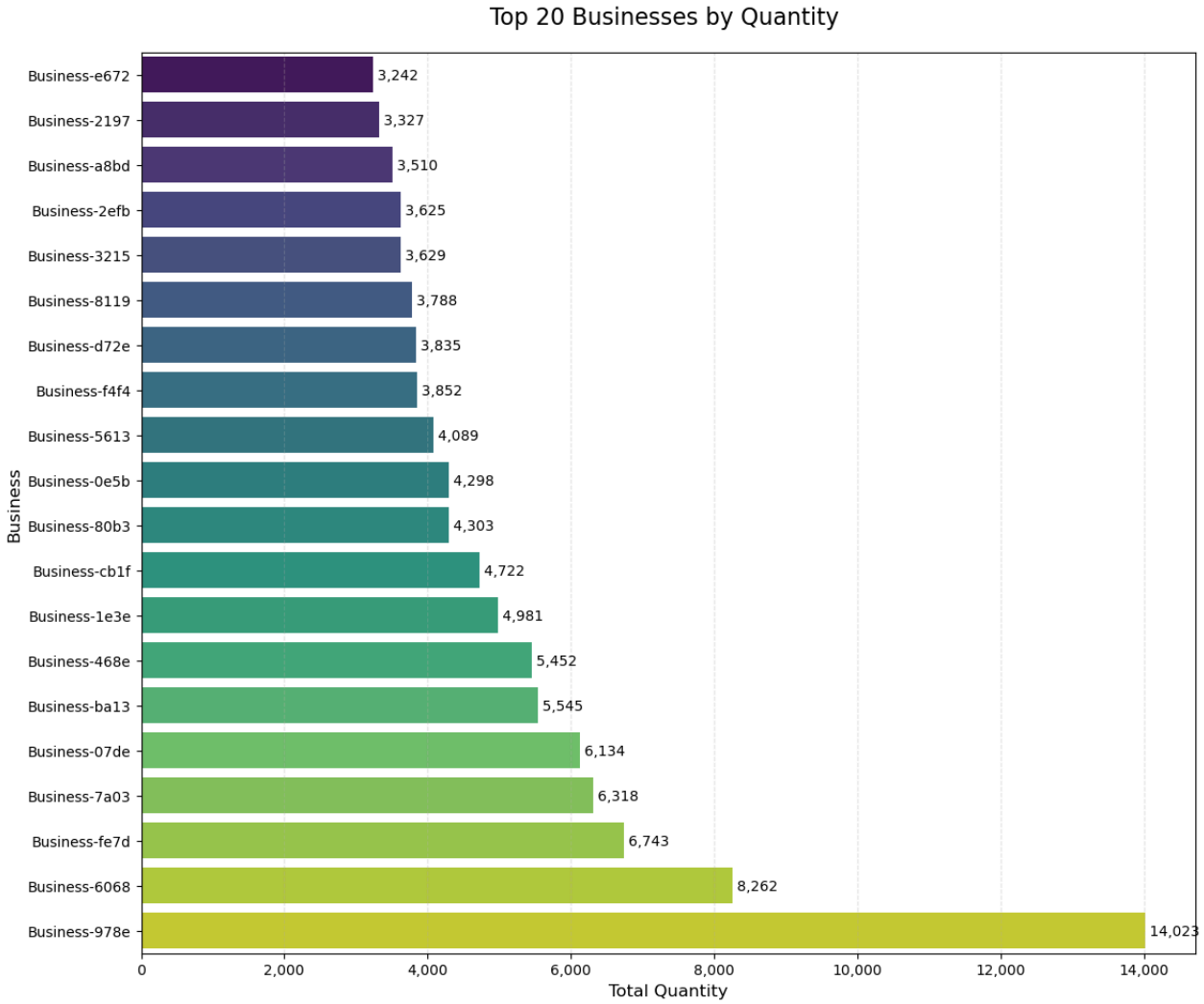


In [45]:
```
# Sort values in descending order
sales_by_category_sorted = sales_by_category.sort_values('Total_Value', ascending=False)

# Create a figure  size
plt.figure(figsize=(15, 8))

# Create the bar plot
sns.barplot(x='Anonymized category', y='Total_Value', data=sales_by_category_sorted)

# Rotate x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

# Format y-axis labels to show full numbers instead of scientific notation
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda x, p: format(int(x), ',')))

# Add title and labels
plt.title('Total Value by Category (Full Values)', pad=20)
plt.xlabel('Category')
plt.ylabel('Total Value')

# Adjust layout to prevent label cutoff
plt.tight_layout()
```



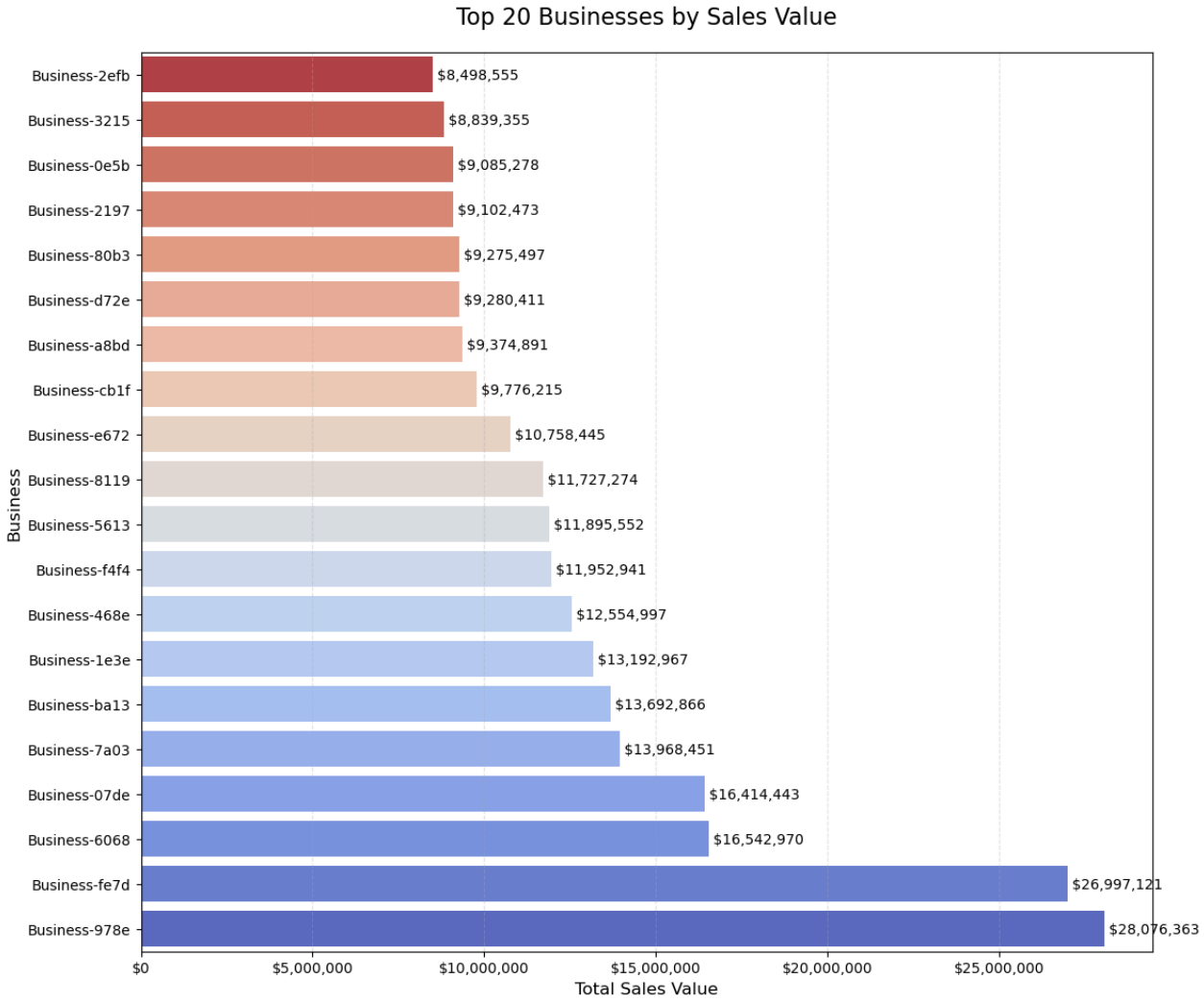
In [46]:

```
# Sort and get top 20 businesses
top_businesses = sales_by_business.sort_values('Quantity', ascending=True).tail(20)

# Create figure with larger width for business names
plt.figure(figsize=(12, 10))

# Create horizontal bar plot
sns.barplot(y='Anonymized business',
            x='Quantity',
            data=top_businesses,
            palette='viridis')

# Customize the plot
plt.title('Top 20 Businesses by Quantity ', fontsize=16, pad=20)
plt.xlabel('Total Quantity', fontsize=12)
plt.ylabel('Business', fontsize=12)

# Format x-axis with comma separator for thousands
plt.gca().xaxis.set_major_formatter(plt.FuncFormatter(lambda x, p: format(int(x), ',')))

# Add gridlines for better readability
plt.grid(axis='x', linestyle='--', alpha=0.3)

# Add value labels at the end of each bar
for i, v in enumerate(top_businesses['Quantity']):
    plt.text(v, i, f' {v:,}', va='center')

# Adjust layout to prevent label cutoff
plt.tight_layout()
```

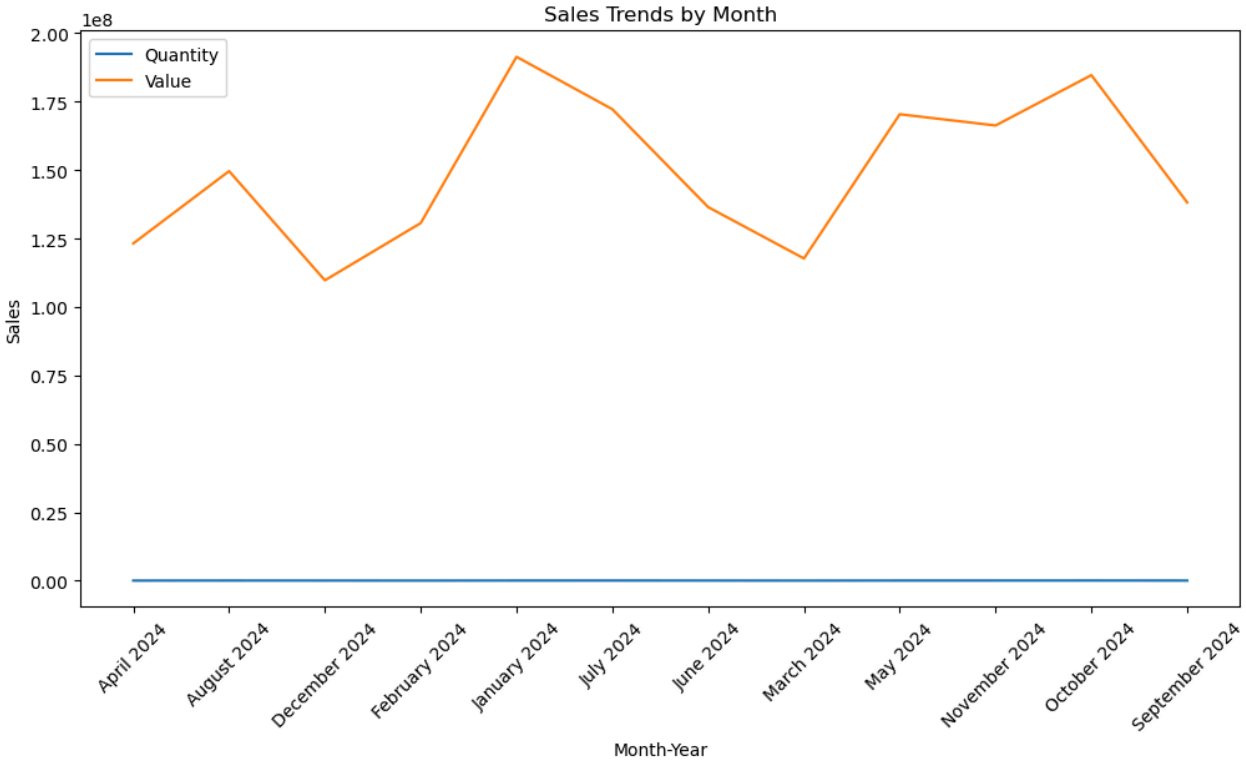

Top 20 Businesses by Quantity
Business
Business-e672
Business-2197
Business-a8bd
Business-2efb
Business-3215
Business-8119
Business-d72e
Business-f4f4
Business-5613
Business-0e5b
Business-80b3
Business-cb1f
Business-1e3e
Business-468e
Business-ba13
Business-07de
Business-7a03
Business-fe7d
Business-6068
Business-978e
3,242
3,327
3,510
3,625
3,629
3,788
3,835
3,852
4,089
4,298
4,303
4,722
4,981
5,452
5,545
6,134
6,318
6,743
8,262
14,023
0
2,000
4,000
6,000
8,000
10,000
12,000
14,000
Total Quantity

In [47]:

```
# Sort by Total_Value and get top 20
top_businesses = sales_by_business.sort_values('Total_Value', ascending=True).tail(20)

# Create figure size
plt.figure(figsize=(12, 10))

# Create horizontal bar plot
sns.barplot(y='Anonymized business',
            x='Total_Value',
            data=top_businesses,
            palette='coolwarm_r')  # Reversed coolwarm palette

# Customize the plot
plt.title('Top 20 Businesses by Sales Value', fontsize=16, pad=20)
plt.xlabel('Total Sales Value', fontsize=12)
plt.ylabel('Business', fontsize=12)

# Format axis with comma separator for thousands
plt.gca().xaxis.set_major_formatter(plt.FuncFormatter(lambda x, p: f'${x:,.0f}'))

# Add gridlines
plt.grid(axis='x', linestyle='--', alpha=0.3)

# Add value labels at the end of each bar
for i, v in enumerate(top_businesses['Total_Value']):
    plt.text(v, i, f' ${v:,.0f}', va='center')

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```


Top 20 Businesses by Sales Value
Business
Business-2efb
Business-3215
Business-0e5b
Business-2197
Business-80b3
Business-d72e
Business-a8bd
Business-cb1f
Business-e672
Business-8119
Business-5613
Business-f4f4
Business-468e
Business-1e3e
Business-ba13
Business-7a03
Business-07de
Business-6068
Business-fe7d
Business-978e
$8,498,555
$8,839,355
$9,085,278
$9,102,473
$9,275,497
$9,280,411
$9,374,891
$9,776,215
$10,758,445
$11,727,274
$11,895,552
$11,952,941
$12,554,997
$13,192,967
$13,692,866
$13,968,451
$16,414,443
$16,542,970
$26,997,121
$28,076,363
$0
$5,000,000
$10,000,000
$15,000,000
$20,000,000
$25,000,000
Total Sales Value

In [48]:
```
# Analyze monthly sales trends

monthly_sales = df1.groupby('Month-Year').agg({
    'Quantity': 'sum',
    'Total_Value': 'sum'
}).reset_index()
#Sort vales by month-year
monthly_sales = monthly_sales.sort_values('Month-Year')

# Create line plot
plt.figure(figsize=(12, 6))
plt.plot(monthly_sales['Month-Year'], monthly_sales['Quantity'])
plt.plot(monthly_sales['Month-Year'], monthly_sales['Total_Value'])
plt.title('Sales Trends by Month')
plt.xlabel('Month-Year')
plt.ylabel('Sales')
plt.legend(['Quantity', 'Value'])
plt.xticks(rotation=45)
plt.show()
```



In [49]:
```
# Top 5 most frequently purchased products
top_quantity_products = df1.groupby('Anonymized product').agg({
    'Quantity': 'sum'
}).nlargest(5, 'Quantity')
print("Top 5 Most Frequently Purchased Products:")
print(top_quantity_products)

# Top 5 most valuable products
top_value_products = df1.groupby('Anonymized product').agg({
    'Total_Value': 'sum'
}).nlargest(5, 'Total_Value')
print("\nTop 5 Most Valuable Products:")
print(top_value_products)
```

```
Top 5 Most Frequently Purchased Products:
                    Quantity
Anonymized product
Product-66e0           47170
Product-e805           43577
Product-8f75           38032
Product-29ee           36639
Product-4156           28704

Top 5 Most Valuable Products:
                    Total_Value
Anonymized product
Product-e805        268760281.0
Product-8f75        160773305.0
Product-66e0         71038955.0
Product-29ee         69722392.0
Product-4156         57413221.0
```

The most frequently bought product is Product-66e0 and the most valuable product is Product-e805 with sales value of 268,760,281.00.

Segmentation Analysis

In [50]:
```
# Group the dataset by 'Anonymized business' to calculate key business metrics
# Sum up the total quantity sold per business
 # Sum up the total sales value per business
 # Count the number of transactions per business
 # Rename 'Date' count to 'Transaction_Frequency' for clarity
business_metrics = df.groupby('Anonymized business').agg({

    'Quantity': 'sum',

    'Total_Value': 'sum',

    'Date': 'count'
}).rename(columns={'Date': 'Transaction_Frequency'})
```

In [51]:
```
## Initialize the scaler
scaler = StandardScaler()
 #Apply standard scaling (zero mean, unit variance) to business metrics
scaled_metrics = scaler.fit_transform(business_metrics)
```

In [53]:
```
## Apply K-Means clustering to segment businesses into 3 clusters
# Initialize KMeans with 3 clusters and a fixed random state for reproducibility
# Fit the model to the scaled metrics
kmeans = KMeans(n_clusters=3, random_state=42)
business_metrics['Segment'] = kmeans.fit_predict(scaled_metrics)
# Mapping cluster numbers to descriptive labels
# Replace numerical segment labels with descriptive names
segment_map = {0: 'Low', 1: 'Medium', 2: 'High'}
business_metrics['Segment_Label'] = business_metrics['Segment'].map(segment_map)
```

Business Classification

High Value Businesses:

These businesses generate the highest sales volume and revenue, often attracting premium clients. To strengthen their loyalty and maximize long-term value, the following strategies are recommended:

- Offer loyalty programs such as rewards and ensure personalized account management, provide customized products/services to strengthen the valuable customer relationships.
- Develop bespoke offerings that cater to their specific needs, reinforcing their commitment to the brand.

Medium Value Businesses:

These businesses contribute to stable and consistent sales, making them a important for growth. Engagement strategies should focus on increasing purchase frequency:

- Provide volume discounts for bulk orders and target them with promotions for complementary products to increase their loyalty.
- Implement personalized marketing campaigns based on their purchase history to encourage repeat business.

Low Value Businesses:

These businesses have a lower overall contribution to revenue but present opportunities for growth and re-engagement. The engagement strategies should focus on nurturing their interest and increasing their purchasing frequency:

- Work on re-engaging them through cost-effective marketing campaigns like reactivation emails and social media ads can help grow their purchase activity over time.
- Provide free samples, limited-time discounts, or entry-level products to encourage initial purchases.

Forecasting

In [39]:
```
#from statsmodels.tsa.holtwinters import ExponentialSmoothing
#from statsmodels.tsa.arima.model import ARIMA
```

In [54]:
```
# ensure correct data type for our analysis
df1['Date'] = pd.to_datetime(df1['Date'])
```

In [55]:
```
#confirm the d -types
df1.dtypes
```

Out[55]:
```
Date                    datetime64[ns]
Anonymized category             object
Anonymized product              object
Anonymized business             object
Anonymized location             object
Quantity                         int64
UnitPrice                      float64
Total_Value                    float64
Month-Year                      object
dtype: object
```

In [56]:
```
# Group sales data by 'Month-Year' and calculate the total sales value for each month
monthly_sales = df1.groupby('Month-Year',).agg({'Total_Value': 'sum'}).reset_index()
monthly_sales
```

Out[56]:

	Month-Year	Total_Value
0	April 2024	123188281.0
1	August 2024	149600209.0
2	December 2024	109713119.0
3	February 2024	130626309.0
4	January 2024	191349182.0
5	July 2024	172210289.0
6	June 2024	136459712.0
7	March 2024	117696757.0
8	May 2024	170372397.0
9	November 2024	166267139.0
10	October 2024	184655201.0
11	September 2024	138160705.0

In [57]:
```
# Reset index to start from 1 instead of 0
monthly_sales.index = monthly_sales.index + 1
monthly_sales
```

Out[57]:

	Month-Year	Total_Value
1	April 2024	123188281.0
2	August 2024	149600209.0
3	December 2024	109713119.0
4	February 2024	130626309.0
5	January 2024	191349182.0
6	July 2024	172210289.0
7	June 2024	136459712.0
8	March 2024	117696757.0
9	May 2024	170372397.0
10	November 2024	166267139.0
11	October 2024	184655201.0

In [59]:
```
# import required library
from statsmodels.tsa.arima.model import ARIMA
```

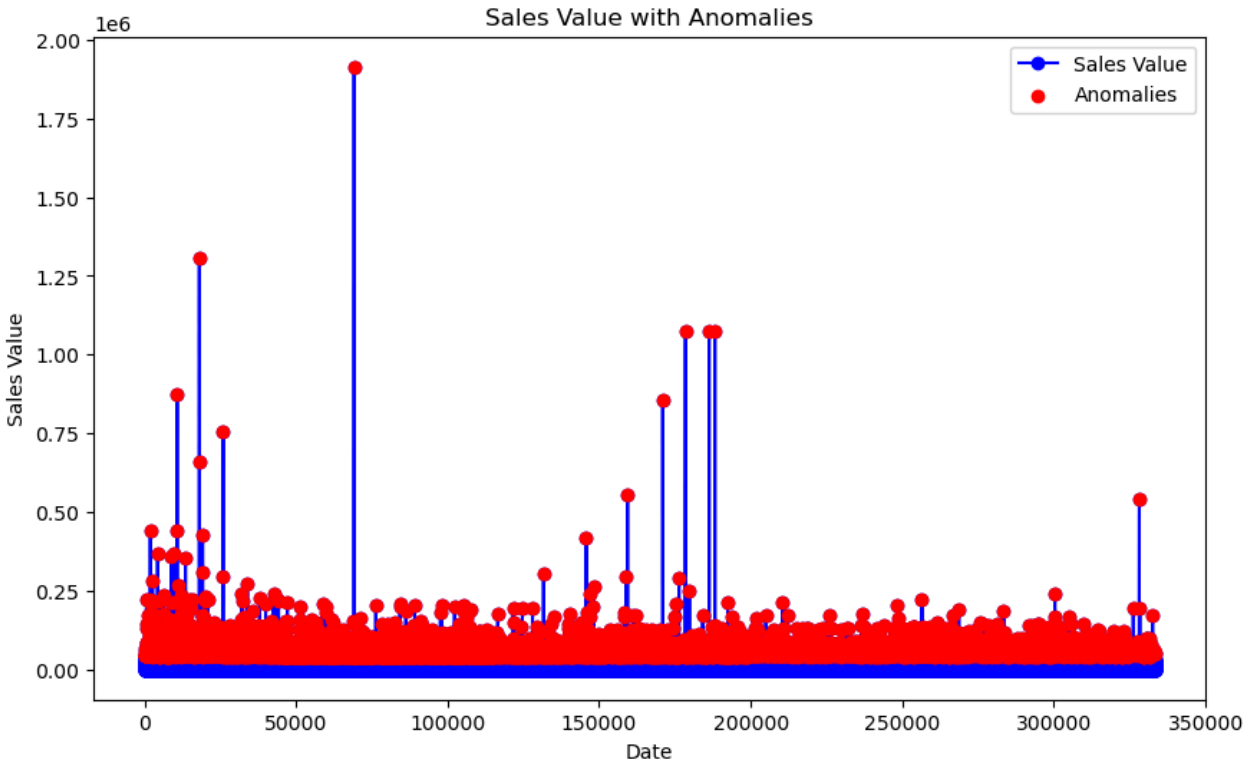
In [60]:
```
# Train ARIMA model with specified order (p=1, d=0, q=1)
# Forecast the next 3 periods (months)
model = ARIMA(monthly_sales['Total_Value'], order=(1,0,1)).fit()
forecast = model.forecast(3)
# Print the forecasted values
print(forecast)
```

```
13    1.435663e+08
14    1.506146e+08
15    1.488316e+08
Name: predicted_mean, dtype: float64
```

The ARIMA model forecasts the following sales value for the next 3 months; 143,566,300 150,614,600 148,831,600

Anomalies Detection

In [61]:
```
# Calculate Z-scores to detect anomalies
df1['Z-Score'] = (df1['Total_Value'] - df1['Total_Value'].mean()) / df1['Total_Value'].std()

# Flag anomalies (e.g., Z-Score > 3 or < -3)
df1['Anomaly'] = df1['Z-Score'].apply(lambda x: True if abs(x) > 3 else False)

# Plot the data with anomalies highlighted
plt.figure(figsize=(10, 6))
plt.plot(df1.index, df1['Total_Value'], label='Sales Value', color='blue', marker='o')
plt.scatter(df1.index[df1['Anomaly']], df1['Total_Value'][df1['Anomaly']],
            color='red', label='Anomalies', zorder=5)
plt.title("Sales Value with Anomalies")
plt.xlabel("Date")
plt.ylabel("Sales Value")
plt.legend()
plt.show()

# Output the anomalies for investigation
print("Anomalies Detected:")
print(df1[df1['Anomaly']])
```



```
Anomalies Detected:
             Date Anonymized category Anonymized product Anonymized business  \
37     2024-01-03         Category-75       Product-1609       Business-dcd4
112    2024-01-02         Category-75       Product-8f75       Business-1a5e
115    2024-01-15         Category-75       Product-1196       Business-95a5
132    2024-01-05         Category-75       Product-8f75       Business-80b3
135    2024-01-05         Category-76       Product-e805       Business-80b3
...           ...                 ...               ...                 ...
332519 2024-12-31         Category-91       Product-3f76       Business-d7ac
332973 2024-12-02         Category-75       Product-8b75       Business-4fcb
333064 2024-12-04         Category-77       Product-b1c8       Business-1e3e
333227 2024-12-17        Category-100       Product-e729       Business-a427
333268 2024-12-11        Category-100       Product-572d       Business-6037

       Anonymized location  Quantity  UnitPrice  Total_Value     Month-Year  \
37           Location-6e9b        10     4350.0      43500.0   January 2024
112          Location-66f4        10     4330.0      43300.0   January 2024
115          Location-0451        10     4400.0      44000.0   January 2024
132          Location-f37d        10     4310.0      43100.0   January 2024
135          Location-f37d         8     7320.0      58560.0   January 2024
...                    ...       ...        ...          ...           ...
332519       Location-7f37        69     2500.0     172500.0  December 2024
332973       Location-21c7        12     4890.0      58680.0  December 2024
333064       Location-03fc        25     2555.0      63875.0  December 2024
333227       Location-1ea3        27     1790.0      48330.0  December 2024
333268       Location-62b5        30     1725.0      51750.0  December 2024

          Z-Score  Anomaly
37       3.393513     True
112      3.375714     True
115      3.438012     True
132      3.357914     True
135      4.733827     True
...           ...      ...
332519  14.874283     True
332973   4.744506     True
333064   5.206852     True
333227   3.823375     True
333268   4.127749     True

[4267 rows x 11 columns]
```

There are anomalies indicated by unusual spikes and drops in sales performance based on Value and Quantity.

Unusual Spikes & unusual drops:

The sudden increase in sales during a specific month might indicate a successful promotional eventor marketing campaign.

Seasons such as holidays can lead to a spike or rise sales.

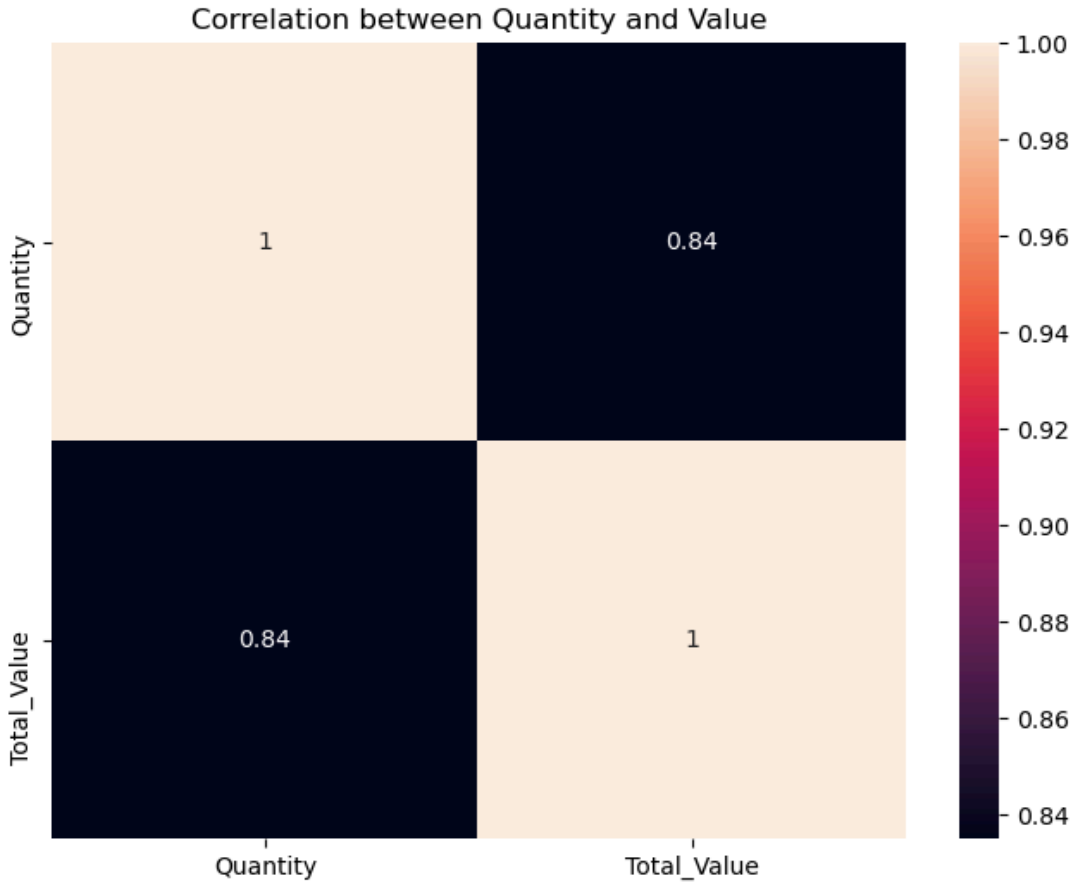
A drop in sales might be due to inventory issues or supply chain disruptions that lead to stock shortage.

A decrease in demand could be due to competitor activity(market competition) or new product launches by rivals thus affecting the business sales.

Correlation Analysis

In [63]:
```
# define a function to perform correlation analysis between 'Quantity' and 'Total_Value'
# Compute the correlation matrix for Quantity and Total_Value
def correlation_analysis(df1):
    correlation = df1[['Quantity', 'Total_Value']].corr()
    #the figure size
    plt.figure(figsize=(8,6))
    # Create a heatmap
    sns.heatmap(correlation, annot=True)
    # label title to the heatmap
    plt.title('Correlation between Quantity and Value')

    return correlation
```

In [64]:
```
correlation = correlation_analysis(df1)
```



In [65]:
```
# # Correlation coefficient
correlation = df1[['Quantity', 'Total_Value']].corr()
correlation
```

Out[65]:

	Quantity	Total_Value
Quantity	1.000000	0.835122
Total_Value	0.835122	1.000000

The correlation coefficient of 0.835 indicates a strong positive relationship between Quantity and Value. As the Quantity of the products sold increases, the total value of sales tends to increase. This is potentially driven by discounts or promotions encouraging bulk purchases or high-demand products.

Factors Driving Sales Performance:

1. Quality of the products: The quality of the products could encourage larger purchases thus boosting both quantity sold and the sales value.
2. Seasonality: Specific times of the year may result to higher sales in quantity and value, influenced by holidays or trends.
3. Marketing strategies and promotions: Effective marketing campaigns increase awareness and as a result drive both quantity and value. Promotions may also encourage bulk purcahses.
4. Pricing: Premium pricing leads to increase in Value per sale while lower prices may result to higher quantities sold.

STRATEGIC INSIGHTS AND RECOMMENDATIONS

Product Strategy

In [63]:
```
# Grouping by Product Category to calculate total sales value and quantity sold
category_stats = df1.groupby('Anonymized category').agg(
    Total_Sales_Value=('Total_Value', 'sum'),
    Total_Quantity=('Quantity', 'sum')
).reset_index()

# Calculate Revenue Contribution (percentage of total sales value)
total_sales = category_stats['Total_Sales_Value'].sum()
category_stats['Revenue_Contribution'] = (category_stats['Total_Sales_Value'] / total_sales) * 1

# Rank categories by Sales Value and Quantity Sold (based on your prioritization criteria)
category_stats['Sales_Rank'] = category_stats['Total_Sales_Value'].rank(ascending=False)
category_stats['Quantity_Rank'] = category_stats['Total_Quantity'].rank(ascending=False)

# Sorting the DataFrame by both Sales and Quantity Rank (Higher ranks are more important)
category_stats = category_stats.sort_values(by=['Sales_Rank', 'Quantity_Rank'])
```

In [65]:
```
# Identify the top-performing product category
top_category = category_stats.iloc[0]
print("\nRecommended Category for Marketing: ", top_category['Anonymized category'])
```

```
Recommended Category for Marketing:  Category-75
```

In [66]:
```
# Display the DataFrame showing the calculated values
print(category_stats)
```

	Anonymized category	Total_Sales_Value	Total_Quantity	Revenue_Contribution	Sales_Rank	Quantity_Rank
25	Category-75	549509348.0	152643	30.693714	1.0	2.0
26	Category-76	351827338.0	72928	19.651873	2.0	4.0
18	Category-120	322737950.0	171443	18.027039	3.0	1.0
0	Category-100	136417463.0	77704	7.619813	4.0	3.0
17	Category-119	103900839.0	68615	5.803546	5.0	5.0
27	Category-77	77791642.0	28825	4.345175	6.0	6.0
38	Category-91	44700098.0	21081	2.496795	7.0	9.0
1	Category-101	35964827.0	19782	2.008872	8.0	10.0
34	Category-85	34298630.0	23368	1.915804	9.0	8.0
19	Category-121	22677154.0	14936	1.266668	10.0	11.0
40	Category-94	16809234.0	23747	0.938906	11.0	7.0
39	Category-92	10595173.0	7037	0.591810	12.0	16.0
28	Category-78	9919076.0	9876	0.554046	13.0	14.0
41	Category-95	7546746.0	4156	0.421535	14.0	20.0
33	Category-84	6852610.0	12029	0.382763	15.0	12.0
5	Category-106	5986975.0	6582	0.334412	16.0	18.0
9	Category-110	5583150.0	10614	0.311856	17.0	13.0
7	Category-108	5159195.0	9782			
10	Category-111	4495262.0	6867			
6	Category-107	4211267.0	2756			
32	Category-83	4058683.0	2445			
31	Category-82	3980705.0	4819			
20	Category-122	3493480.0	1223			
4	Category-105	2844024.0	1656			
43	Category-97	2657369.0	2796			
44	Category-98	2520065.0	2153			
42	Category-96	2313675.0	1445			
24	Category-74	1934051.0	944			
45	Category-99	1595410.0	1969			
3	Category-104	1564133.0	1222			
8	Category-109	1269541.0	1453			
11	Category-113	1257258.0	752			
29	Category-79	1188062.0	2220			
21	Category-123	730730.0	286			
2	Category-102	501824.0	1941			
13	Category-115	428430.0	349			
14	Category-116	422745.0	856			
23	Category-125	297060.0	123			
36	Category-89	138575.0	241			
30	Category-81	72663.0	144			
37	Category-90	15750.0	15			
22	Category-124	10060.0	4			
12	Category-114	8600.0	3			
16	Category-118	7560.0	21			
35	Category-86	3320.0	8			
15	Category-117	1550.0	5			

7	0.288175	18.0	15.0
10	0.251090	19.0	17.0
6	0.235227	20.0	22.0
32	0.226704	21.0	23.0
31	0.222349	22.0	19.0
20	0.195134	23.0	31.0
4	0.158857	24.0	28.0
43	0.148432	25.0	21.0
44	0.140762	26.0	25.0
42	0.129234	27.0	30.0
24	0.108029	28.0	33.0
45	0.089114	29.0	26.0
3	0.087367	30.0	32.0
8	0.070912	31.0	29.0
11	0.070226	32.0	35.0
29	0.066361	33.0	24.0
21	0.040816	34.0	37.0
2	0.028030	35.0	27.0
13	0.023931	36.0	36.0
14	0.023613	37.0	34.0
23	0.016593	38.0	40.0
36	0.007740	39.0	38.0
30	0.004059	40.0	39.0
37	0.000880	41.0	42.0
22	0.000562	42.0	45.0
12	0.000480	43.0	46.0
16	0.000422	44.0	41.0
35	0.000185	45.0	43.0
15	0.000087	46.0	44.0

The category-75 has the highest revenue contribution and quantity sold, making it the top-performing category. Therefore,this category should be prioritized for marketing and promotion campaigns due to its high sales volume, revenue generation and customer demand.

Customer Retention

In [91]:
```
# Convert 'Month-Year' to datetime
df1['Month-Year'] = pd.to_datetime(df1['Month-Year'], format='%B %Y')

# Calculate the frequency of purchases per business per month
df1['Month'] = df1['Month-Year'].dt.to_period('M')  # Extract the month and year

# Count purchases per business per month
business_monthly_purchase = df1.groupby(['Anonymized business', 'Month']).size().reset_index(nam

# Pivot to create a matrix of business purchase frequency per month
business_monthly_purchase_pivot = business_monthly_purchase.pivot(index='Anonymized business', c

# Calculate the trend of purchase frequency by comparing the last month's frequency with earlier
business_monthly_purchase_pivot['Frequency Trend'] = business_monthly_purchase_pivot.apply(
    lambda row: 'Decreasing' if row.iloc[-1] < row.iloc[0] else 'Stable/Increasing', axis=1
)

# Display businesses with decreasing purchase frequency
decreasing_businesses = business_monthly_purchase_pivot[business_monthly_purchase_pivot['Frequen
print(decreasing_businesses)
```

Month	2024-01	2024-02	2024-03	2024-04	2024-05	2024-06	\
Anonymized business							
Business-00f8	5.0	5.0	0.0	0.0	0.0	0.0	
Business-016c	48.0	35.0	39.0	27.0	39.0	41.0	
Business-0197	9.0	0.0	0.0	0.0	0.0	0.0	
Business-01de	67.0	21.0	19.0	0.0	18.0	22.0	
Business-0204	44.0	33.0	26.0	8.0	16.0	19.0	
...	...	...	...	...	...	...	
Business-fe7d	57.0	33.0	60.0	43.0	62.0	32.0	
Business-fed0	13.0	17.0	5.0	8.0	9.0	0.0	
Business-fef1	135.0	134.0	158.0	110.0	95.0	65.0	
Business-ff19	10.0	1.0	0.0	0.0	0.0	0.0	
Business-ffb1	43.0	25.0	14.0	0.0	0.0	0.0	

Month	2024-07	2024-08	2024-09	2024-10	2024-11	2024-12	\
Anonymized business							
Business-00f8	0.0	0.0	0.0	0.0	0.0	0.0	
Business-016c	26.0	44.0	42.0	28.0	28.0	40.0	
Business-0197	0.0	0.0	0.0	0.0	0.0	0.0	
Business-01de	0.0	0.0	0.0	0.0	0.0	0.0	
Business-0204	9.0	8.0	0.0	3.0	0.0	0.0	
...	...	...	...	...	...	...	
Business-fe7d	46.0	45.0	72.0	79.0	90.0	34.0	
Business-fed0	0.0	0.0	5.0	2.0	0.0	0.0	
Business-fef1	68.0	69.0	87.0	103.0	54.0	97.0	
Business-ff19	0.0	0.0	0.0	0.0	0.0	0.0	
Business-ffb1	0.0	0.0	8.0	15.0	0.0	0.0	

Month	Frequency Trend
Anonymized business	
Business-00f8	Decreasing
Business-016c	Decreasing
Business-0197	Decreasing
Business-01de	Decreasing
Business-0204	Decreasing
...	...
Business-fe7d	Decreasing
Business-fed0	Decreasing
Business-fef1	Decreasing
Business-ff19	Decreasing
Business-ffb1	Decreasing

[954 rows x 13 columns]

Re-engagement Strategies for Businesses with Decreased Purchase Frequency:

📌 Personalized Outreaches: Send personalized emails, share offer deals or discounts information for businesses with low purchases. Introduce account managers for a more personal connection.

📌 Discounts and Offers: Provide discounts that are available for a limited period to create urgency and drive traffic. Offer discounts on bulk purchases to encourage high order volumes which will boost the sales.

📌 Loyalty: Create loyalty programs that rewards businesses with points or discounts for repeat purchases to encourage long-term relationships.

📌 Targeted Promotions: Allow access to the newly launched products and highlight the new product arrivals that might be of interest to the business. Effectively share updates about any improvements in the product range, customizations or upgardes that can appeal to the business.

📌 Seasons: Provide offers, special promotions or discounts based on the times of the year especially for seasonal products that are relevant to the business.

📌 Feedback: Reach out to understand why the frequency of purchases has decreased and also send a surveys or directly inquire about any challenges they might be facing. Offer solutions or incentives based on the feedback received to improve their satisfaction and restore the frequency of purchases.

Operational Efficiency

In [99]:
```
# Calculate total sales for each product based on Quantity and UnitPrice
df1['Total_Sales'] = df1['Quantity'] * df1['UnitPrice']

# Group data by product to get total sales and quantity sold over time
product_performance = df1.groupby(['Anonymized product', 'Month-Year']).agg(
    Total_Sales=('Total_Sales', 'sum'),
    Total_Quantity_Sold=('Quantity', 'sum')
).reset_index()

# Pivot data for better analysis of sales performance by product
product_performance_pivot = product_performance.pivot(
    index='Anonymized product', columns='Month-Year', values='Total_Sales').fillna(0)
```

In [100]:
```
# Identify best-performing products (based on total sales) and worst-performing products
best_performing_products = product_performance_pivot.sum(axis=1).sort_values(ascending=False)
worst_performing_products = product_performance_pivot.sum(axis=1).sort_values(ascending=True)

print("Best Performing Products:\n", best_performing_products.head())
print("Worst Performing Products:\n", worst_performing_products.head())
```

```
Best Performing Products:
 Anonymized product
Product-e805    268760281.0
Product-8f75    160773305.0
Product-66e0     71038955.0
Product-29ee     69722392.0
Product-4156     57413221.0
dtype: float64
Worst Performing Products:
 Anonymized product
Product-9393    0.0
Product-c1d6    0.0
Product-da0e    0.0
Product-38e9    0.0
Product-3dcf    0.0
dtype: float64
```

In [107]:
```
# Calculate the average sales per product
product_performance['Avg_Sales'] = product_performance.groupby('Anonymized product')['Total_Sale

# Define a threshold for restocking (e.g., if total sales fall below average sales)
restock_threshold = product_performance[product_performance['Total_Sales'] < product_performance

print("Restocking Needed Products:\n", restock_threshold[['Anonymized product', 'Total_Sales', '
```

```
Restocking Needed Products:
      Anonymized product  Total_Sales      Avg_Sales
2          Product-004f       9760.0   13013.333333
5          Product-02e4       9360.0   14655.000000
8          Product-02e4      10780.0   14655.000000
10         Product-031c      12900.0  219466.363636
11         Product-031c     102510.0  219466.363636
...                 ...          ...            ...
3635       Product-ff95     337680.0  433452.222222
3636       Product-ff95     372960.0  433452.222222
3639       Product-ff95     410360.0  433452.222222
3643       Product-ffa6      13675.0   41920.000000
3645       Product-ffb7          0.0     560.000000

[1850 rows x 3 columns]
```

The analysis above shows that fast- selling products such as Product-004f, Product-02e4, Product-031c and Product-ff95 have total sales value below average indicating that they are selling out faster than they are restocked. This coud lead to customer dissatisfaction.

In [105]:

```
# Group by product and month-year to get the total sales per product per month
seasonal_demand = df1.groupby(['Anonymized product', 'Month-Year']).agg(
    Total_Sales=('Total_Value', 'sum')
).reset_index()

# Pivot data to have months as columns
seasonal_demand_pivot = seasonal_demand.pivot(
    index='Anonymized product', columns='Month-Year', values='Total_Sales').fillna(0)

# Calculate the average sales per month for each product
seasonal_demand_pivot['Avg_Sales'] = seasonal_demand_pivot.mean(axis=1)

# Identify months with higher sales than the average
seasonal_peaks = seasonal_demand_pivot.loc[:, seasonal_demand_pivot.columns != 'Avg_Sales']
#seasonal_peaks = seasonal_peaks.apply(lambda x: x > seasonal_demand_pivot['Avg_Sales'].to_numpy
seasonal_peaks = seasonal_peaks > seasonal_demand_pivot['Avg_Sales'].values[:, None]


print("Seasonal Demand Peaks for Products:\n", seasonal_peaks)
```

Seasonal Demand Peaks for Products:

Month-Year	2024-01-01 00:00:00	2024-02-01 00:00:00	\
Anonymized product			
Product-0001	False	False	
Product-0031	True	False	
Product-004f	False	False	
Product-02e4	False	False	
Product-031c	True	False	
...	...	...	
Product-fee0	True	False	
Product-ff72	False	False	
Product-ff95	False	False	
Product-ffa6	False	False	
Product-ffb7	False	False	

Month-Year	2024-03-01 00:00:00	2024-04-01 00:00:00	\
Anonymized product			
Product-0001	False	False	
Product-0031	False	False	
Product-004f	False	False	
Product-02e4	False	False	
Product-031c	False	False	
...	...	...	
Product-fee0	False	False	
Product-ff72	False	False	
Product-ff95	False	False	
Product-ffa6	False	False	
Product-ffb7	False	False	

Month-Year	2024-05-01 00:00:00	2024-06-01 00:00:00	\
Anonymized product			
Product-0001	False	False	
Product-0031	False	False	
Product-004f	False	False	
Product-02e4	False	False	
Product-031c	True	True	
...	...	...	
Product-fee0	False	False	
Product-ff72	False	False	
Product-ff95	True	True	
Product-ffa6	False	False	
Product-ffb7	False	False	

Month-Year	2024-07-01 00:00:00	2024-08-01 00:00:00	\
Anonymized product			
Product-0001	False	False	
Product-0031	False	False	
Product-004f	False	True	
Product-02e4	False	False	
Product-031c	True	False	
...	...	...	
Product-fee0	False	False	
Product-ff72	False	False	
Product-ff95	True	True	
Product-ffa6	True	False	
Product-ffb7	False	False	

Month-Year	2024-09-01 00:00:00	2024-10-01 00:00:00	\
Anonymized product			
Product-0001	False	False	
Product-0031	False	False	
Product-004f	True	True	
Product-02e4	True	True	
Product-031c	False	False	
...	...	...	
Product-fee0	False	False	

```
Product-ff72                      False                False
Product-ff95                       True                 True
Product-ffa6                      False                False
Product-ffb7                       True                False

Month-Year          2024-11-01 00:00:00  2024-12-01 00:00:00
Anonymized product
Product-0001                      False                 True
Product-0031                      False                False
Product-004f                      False                False
Product-02e4                       True                 True
Product-031c                      False                False
...                                 ...                  ...
Product-fee0                      False                False
Product-ff72                       True                 True
Product-ff95                       True                 True
Product-ffa6                      False                 True
Product-ffb7                      False                False

[817 rows x 12 columns]
```

Seasonal demand anaysis

1. Winter Peaks (Dec – Feb): Products like Product-031c and Product-0001 sells well in January and December respectively. This could be associated with holiday shopping, warm clothing, or seasonal foods.
2. Spring & Summer Demand (Mar – Aug): Product-ff95 and Product-004f does so well in May, June and August respectively. Suggesting demand in summer essentials and outdoor products.
3. Autumn & Back-to-School Surge (Sep – Nov): Product-004f and Product-ff95 see high demand in September & October, likely due to seasonal transitions.
4. Holiday Season & Year-End Demand (Nov – Dec): Product-ffa6 and Product-ff95 sales peak in November & December, reflecting holiday shopping trends and gift-related purchases.

Recommendations to improvements inventory management and supply chain processes:

📌 Pre-stock seasonal products before peak demand periods and prioritize replenishment of low-stock, high-revenue items.

📌 Plan for smaller, frequent restocks for high-demand products to avoid overstocking and ensure you don’t run out of popular items during peak periods.

📌 Investigate stock shortages for products like Product-ffa6 and Product-ffb7 and collaborate with suppliers to reduce lead times and prevent stockouts.

📌 Enhance marketing efforts for underperforming products to boost sales and optimize low-selling Products.

📌 Use historical seasonal trends to improve demand forecasting help in making restocking decisions..