Optimizing Sales Strategy and Customer Engagement for an E-Commerce Store

Modules

In [1]:
```
# Data Proccessing
import pandas as pd
import numpy as np
# Data Visualization
import seaborn as sns
sns.set_theme(
    style="ticks",
    palette="deep",
    font_scale=1.1,
    rc={
        'figure.figsize': (12, 9),
        'figure.facecolor': 'white',
        'axes.spines.right': False,
        'axes.spines.top': False,
        'grid.alpha': 0.3,
        'axes.grid': True,
    }
    )
import matplotlib.pyplot as plt
# Regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.model_selection import train_test_split, cross_val_score
#
import warnings
warnings.filterwarnings('ignore')
```

Reading Data

In [2]:
```
df = pd.read_csv("/kaggle/input/ecommerce-data/data.csv", encoding='latin-1')
df.head()
```

Out[2]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

Data Processing

Data Types

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 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 
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

Customer ID Preferred to be Object, While InvoiceDate Should be in datetime

In [4]:
```
df['CustomerID'] = df['CustomerID'].astype('object')
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 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  datetime64[ns]
 5   UnitPrice    541909 non-null  float64       
 6   CustomerID   406829 non-null  object        
 7   Country      541909 non-null  object        
dtypes: datetime64[ns](1), float64(1), int64(1), object(5)
memory usage: 33.1+ MB
```

In [6]:
```
# Create Required Columns for analysis
df['Hour'] = df['InvoiceDate'].dt.hour

df['InvoiceDate'] = pd.to_datetime(pd.to_datetime(df['InvoiceDate']).dt.date)
df['Year'] = df['InvoiceDate'].dt.year
df['Month'] = df['InvoiceDate'].dt.month
df['Day_Name'] = df['InvoiceDate'].dt.day_name()
df['TotalPrice'] = df['Quantity']*df['UnitPrice']
```

In [7]:
```
df.head()
```

Out[7]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Hour	Year	Month	Day_Name	TotalPrice
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01	2.55	17850.0	United Kingdom	8	2010	12	Wednesday	15.30
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01	3.39	17850.0	United Kingdom	8	2010	12	Wednesday	20.34
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01	2.75	17850.0	United Kingdom	8	2010	12	Wednesday	22.00
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01	3.39	17850.0	United Kingdom	8	2010	12	Wednesday	20.34
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01	3.39	17850.0	United Kingdom	8	2010	12	Wednesday	20.34

Duplicated Values

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
5269
```

In [9]:
```
true_duplicates = df[df.duplicated(keep=False)]

print(true_duplicates.head(10))
```

```
    InvoiceNo StockCode                       Description  Quantity  \
485    536409     22111       SCOTTIE DOG HOT WATER BOTTLE         1
489    536409     22866      HAND WARMER SCOTTY DOG DESIGN         1
494    536409     21866        UNION JACK FLAG LUGGAGE TAG         1
517    536409     21866        UNION JACK FLAG LUGGAGE TAG         1
521    536409     22900    SET 2 TEA TOWELS I LOVE LONDON          1
527    536409     22866      HAND WARMER SCOTTY DOG DESIGN         1
537    536409     22900    SET 2 TEA TOWELS I LOVE LONDON          1
539    536409     22111       SCOTTIE DOG HOT WATER BOTTLE         1
548    536412     22327  ROUND SNACK BOXES SET OF 4 SKULLS         1
555    536412     22327  ROUND SNACK BOXES SET OF 4 SKULLS         1

    InvoiceDate  UnitPrice CustomerID         Country  Hour  Year  Month  \
485  2010-12-01       4.95    17908.0  United Kingdom    11  2010     12
489  2010-12-01       2.10    17908.0  United Kingdom    11  2010     12
494  2010-12-01       1.25    17908.0  United Kingdom    11  2010     12
517  2010-12-01       1.25    17908.0  United Kingdom    11  2010     12
521  2010-12-01       2.95    17908.0  United Kingdom    11  2010     12
527  2010-12-01       2.10    17908.0  United Kingdom    11  2010     12
537  2010-12-01       2.95    17908.0  United Kingdom    11  2010     12
539  2010-12-01       4.95    17908.0  United Kingdom    11  2010     12
548  2010-12-01       2.95    17920.0  United Kingdom    11  2010     12
555  2010-12-01       2.95    17920.0  United Kingdom    11  2010     12

      Day_Name  TotalPrice
485  Wednesday        4.95
489  Wednesday        2.10
494  Wednesday        1.25
517  Wednesday        1.25
521  Wednesday        2.95
527  Wednesday        2.10
537  Wednesday        2.95
539  Wednesday        4.95
548  Wednesday        2.95
555  Wednesday        2.95
```

Decision: To ensure the accuracy of quantitative analysis, all duplicate rows were removed, keeping only the first occurrence of each unique record.

In [10]:
```
df.drop_duplicates(inplace= True, keep='first')
df.duplicated().sum()
```

Out[10]:
```
0
```

Outliers

In [11]:
```
print(df.describe())
```

```
           Quantity                    InvoiceDate      UnitPrice  \
count  536640.000000                         536640  536640.000000
mean        9.620043  2011-07-03 19:22:15.670840832       4.632661
min    -80995.000000            2010-12-01 00:00:00  -11062.060000
25%         1.000000            2011-03-28 00:00:00       1.250000
50%         3.000000            2011-07-19 00:00:00       2.080000
75%        10.000000            2011-10-18 00:00:00       4.130000
max     80995.000000            2011-12-09 00:00:00   38970.000000
std       219.130360                            NaN      97.233208

                Hour           Year          Month     TotalPrice
count  536640.000000  536640.000000  536640.000000  536640.000000
mean       13.077150    2010.921771       7.544818      18.123888
min         6.000000    2010.000000       1.000000 -168469.600000
25%        11.000000    2011.000000       5.000000       3.750000
50%        13.000000    2011.000000       8.000000       9.870000
75%        15.000000    2011.000000      11.000000      17.400000
max        20.000000    2011.000000      12.000000  168469.600000
std         2.447506       0.268532       3.508699     380.656617
```

In [12]:
```
print(df[df['Quantity'] < 0 ].head())
```

```
    InvoiceNo StockCode                      Description  Quantity  \
141   C536379         D                         Discount        -1
154   C536383    35004C   SET OF 3 COLOURED  FLYING DUCKS        -1
235   C536391     22556    PLASTERS IN TIN CIRCUS PARADE        -12
236   C536391     21984  PACK OF 12 PINK PAISLEY TISSUES        -24
237   C536391     21983  PACK OF 12 BLUE PAISLEY TISSUES        -24

    InvoiceDate  UnitPrice CustomerID         Country  Hour  Year  Month  \
141  2010-12-01      27.50    14527.0  United Kingdom     9  2010     12
154  2010-12-01       4.65    15311.0  United Kingdom     9  2010     12
235  2010-12-01       1.65    17548.0  United Kingdom    10  2010     12
236  2010-12-01       0.29    17548.0  United Kingdom    10  2010     12
237  2010-12-01       0.29    17548.0  United Kingdom    10  2010     12

      Day_Name  TotalPrice
141  Wednesday      -27.50
154  Wednesday       -4.65
235  Wednesday      -19.80
236  Wednesday       -6.96
237  Wednesday       -6.96
```

In [13]:
```
print(df[df['Quantity'] > 10000 ].head())
```

```
       InvoiceNo StockCode                       Description  Quantity  \
61619     541431     23166  MEDIUM CERAMIC TOP STORAGE JAR     74215
502122    578841     84826  ASSTD DESIGN 3D PAPER STICKERS     12540
540421    581483     23843     PAPER CRAFT , LITTLE BIRDIE     80995

       InvoiceDate  UnitPrice CustomerID         Country  Hour  Year  Month  \
61619   2011-01-18       1.04    12346.0  United Kingdom    10  2011      1
502122  2011-11-25       0.00    13256.0  United Kingdom    15  2011     11
540421  2011-12-09       2.08    16446.0  United Kingdom     9  2011     12

       Day_Name  TotalPrice
61619   Tuesday     77183.6
502122   Friday         0.0
540421   Friday    168469.6
```

This almost always represents a cancellation or a return of a product.

These are valid records. They represent money being credited back to the customer.

In [14]:
```
print(df[df['UnitPrice'] < 0 ].head())
```

```
       InvoiceNo StockCode      Description  Quantity InvoiceDate  UnitPrice  \
299983   A563186         B  Adjust bad debt         1  2011-08-12  -11062.06
299984   A563187         B  Adjust bad debt         1  2011-08-12  -11062.06

       CustomerID         Country  Hour  Year  Month Day_Name  TotalPrice
299983        NaN  United Kingdom    14  2011      8   Friday   -11062.06
299984        NaN  United Kingdom    14  2011      8   Friday   -11062.06
```

In [15]:
```
print(df[df['UnitPrice'] > 10000 ].head())
```

```
      InvoiceNo  StockCode Description  Quantity InvoiceDate  UnitPrice  \
15016   C537630  AMAZONFEE  AMAZON FEE        -1  2010-12-07   13541.33
15017    537632  AMAZONFEE  AMAZON FEE         1  2010-12-07   13541.33
16232   C537644  AMAZONFEE  AMAZON FEE        -1  2010-12-07   13474.79
16356   C537651  AMAZONFEE  AMAZON FEE        -1  2010-12-07   13541.33
43702   C540117  AMAZONFEE  AMAZON FEE        -1  2011-01-05   16888.02

      CustomerID         Country  Hour  Year  Month   Day_Name  TotalPrice
15016        NaN  United Kingdom    15  2010     12    Tuesday   -13541.33
15017        NaN  United Kingdom    15  2010     12    Tuesday    13541.33
16232        NaN  United Kingdom    15  2010     12    Tuesday   -13474.79
16356        NaN  United Kingdom    15  2010     12    Tuesday   -13541.33
43702        NaN  United Kingdom     9  2011      1  Wednesday   -16888.02
```

These are also valid, non-product records representing accounting adjustments.

Preparing suitable data for customer, product, and distribution analysis

In [16]:
```
non_product_keywords = ['POSTAGE', 'FEE', 'DISCOUNT', 'ADJUSTMENT', 'CARRIAGE', 'Manual']

# Create a pattern to match any of these keywords in the Description field
pattern = '|'.join(non_product_keywords)
is_non_product = df['Description'].str.contains(pattern, case=False, na=False)

# 1. Calculate Q1, Q3, and IQR
Q1_qty = df['Quantity'].quantile(0.25)
Q3_qty = df['Quantity'].quantile(0.75)
IQR_qty = Q3_qty - Q1_qty

Q1_up = df['UnitPrice'].quantile(0.25)
Q3_up = df['UnitPrice'].quantile(0.75)
IQR_up = Q3_up - Q1_up

# 2. Define the outlier boundaries
upper_bound_qty = Q3_qty + 6 * IQR_qty
upper_bound_up = Q3_up + 6 * IQR_up

# Step 3: Create the clean analysis dataframe for customer behavior
analysis_df = df[
    (df['Quantity'] > 0) &
    (df['Quantity'] <= upper_bound_qty) &
    (df['UnitPrice'] > 0) &
    (df['UnitPrice'] <= upper_bound_up) &
    (~is_non_product)
].copy()
```

In [17]:
```
analysis_df.describe()
```

Out[17]:

	Quantity	InvoiceDate	UnitPrice	Hour	Year	Month	TotalPrice
count	506087.000000	506087	506087.000000	506087.000000	506087.000000	506087.000000	506087.000000
mean	7.075750	2011-07-04 09:29:09.448612352	3.170192	13.092858	2010.921729	7.564616	14.424555
min	1.000000	2010-12-01 00:00:00	0.001000	6.000000	2010.000000	1.000000	0.001000
25%	1.000000	2011-03-28 00:00:00	1.250000	11.000000	2011.000000	5.000000	3.750000
50%	3.000000	2011-07-20 00:00:00	2.080000	13.000000	2011.000000	8.000000	9.480000
75%	10.000000	2011-10-19 00:00:00	4.130000	15.000000	2011.000000	11.000000	17.000000
max	64.000000	2011-12-09 00:00:00	21.230000	20.000000	2011.000000	12.000000	897.750000
std	9.037037	NaN	3.064753	2.437652	0.268598	3.508975	22.137177

Missing Values

In [18]:
```
df.isnull().sum()
```

Out[18]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135037
Country             0
Hour                0
Year                0
Month               0
Day_Name            0
TotalPrice          0
dtype: int64
```

It Appears That 25% of Customer Id Data is missing, this requires Further Analysis to make the right decision

In [19]:
```
# 1. Isolate the rows with missing CustomerID
null_customer_df = df[df['CustomerID'].isna()]

# 2. Compare them to the rows with valid CustomerID
valid_customer_df = df[df['CustomerID'].notna()]
```

In [20]:
```
# 3. Check the Description of these transactions
print("Common items in null CustomerID transactions:")
print(null_customer_df['Description'].value_counts().head(10))
```

```
Common items in null CustomerID transactions:
Description
DOTCOM POSTAGE                      693
JUMBO BAG RED RETROSPOT             497
JUMBO STORAGE BAG SUKI              414
JUMBO SHOPPER VINTAGE RED PAISLEY   388
JUMBO BAG WOODLAND ANIMALS          372
JUMBO BAG PINK POLKADOT             348
RECYCLING BAG RETROSPOT             341
RED TOADSTOOL LED NIGHT LIGHT       328
SUKI  SHOULDER BAG                  326
GREEN REGENCY TEACUP AND SAUCER     324
Name: count, dtype: int64
```

In [21]:
```
# 4. Check if these transactions have specific Invoice numbers
print("Sample of InvoiceNos with null CustomerID:")
print(null_customer_df['InvoiceNo'].astype(str).str[0].value_counts())
```

```
Sample of InvoiceNos with null CustomerID:
InvoiceNo
5    134655
C       379
A         3
Name: count, dtype: int64
```

In [22]:
```
# 5. Compare key metrics
print(f"Average Quantity (Null CustomerID): {null_customer_df['Quantity'].mean()}")
print(f"Average Quantity (Valid CustomerID): {valid_customer_df['Quantity'].mean()}")

print(f"Average UnitPrice (Null CustomerID): {null_customer_df['UnitPrice'].mean()}")
print(f"Average UnitPrice (Valid CustomerID): {valid_customer_df['UnitPrice'].mean()}")
```

```
Average Quantity (Null CustomerID): 1.996867525196798
Average Quantity (Valid CustomerID): 12.183297933531373
Average UnitPrice (Null CustomerID): 8.078342380236528
Average UnitPrice (Valid CustomerID): 3.4740674347552183
```

Data Segmentation (Customers Data and Overall Business Data)

These records represent operational overhead (postage, packaging) and system adjustments (cancellations), not the purchasing behavior of identifiable customers. Therefore, they are removed for analyses focusing on customer segmentation, retention (cohort analysis), and lifetime value (RFM analysis) to avoid skewing the results.

In [23]:
```
customer_df = analysis_df.dropna().copy()
customer_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 377176 entries, 0 to 541908
Data columns (total 13 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    377176 non-null  object        
 1   StockCode    377176 non-null  object        
 2   Description  377176 non-null  object        
 3   Quantity     377176 non-null  int64         
 4   InvoiceDate  377176 non-null  datetime64[ns]
 5   UnitPrice    377176 non-null  float64       
 6   CustomerID   377176 non-null  object        
 7   Country      377176 non-null  object        
 8   Hour         377176 non-null  int32         
 9   Year         377176 non-null  int32         
 10  Month        377176 non-null  int32         
 11  Day_Name     377176 non-null  object        
 12  TotalPrice   377176 non-null  float64       
dtypes: datetime64[ns](1), float64(2), int32(3), int64(1), object(6)
memory usage: 36.0+ MB
```

For calculating total revenue, analyzing sales trends over time, and identifying best-selling product lines, the entire dataset is used. Fees like postage contribute to overall income, and including cancellations is necessary for an accurate financial picture

In [24]:
```
business_df = df.copy()
business_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 536640 entries, 0 to 541908
Data columns (total 13 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    536640 non-null  object        
 1   StockCode    536640 non-null  object        
 2   Description  535186 non-null  object        
 3   Quantity     536640 non-null  int64         
 4   InvoiceDate  536640 non-null  datetime64[ns]
 5   UnitPrice    536640 non-null  float64       
 6   CustomerID   401603 non-null  object        
 7   Country      536640 non-null  object        
 8   Hour         536640 non-null  int32         
 9   Year         536640 non-null  int32         
 10  Month        536640 non-null  int32         
 11  Day_Name     536640 non-null  object        
 12  TotalPrice   536640 non-null  float64       
dtypes: datetime64[ns](1), float64(2), int32(3), int64(1), object(6)
memory usage: 51.2+ MB
```

EDA

Overall financial health of the business

Total Revenue, Total Orders, Average Order Value

In [25]:
```
# Calculate Total Revenue, Total Orders, AOV
total_revenue = sum(business_df['TotalPrice'])
total_orders = business_df['InvoiceNo'].nunique()
aov = total_revenue/total_orders
# Present Fingdings
print(f"Total Revenue: {total_revenue}")
print('')
print(f"Total Orders: {total_orders}")
print('')
print(f"Average Order value: {aov}")
print('')
```

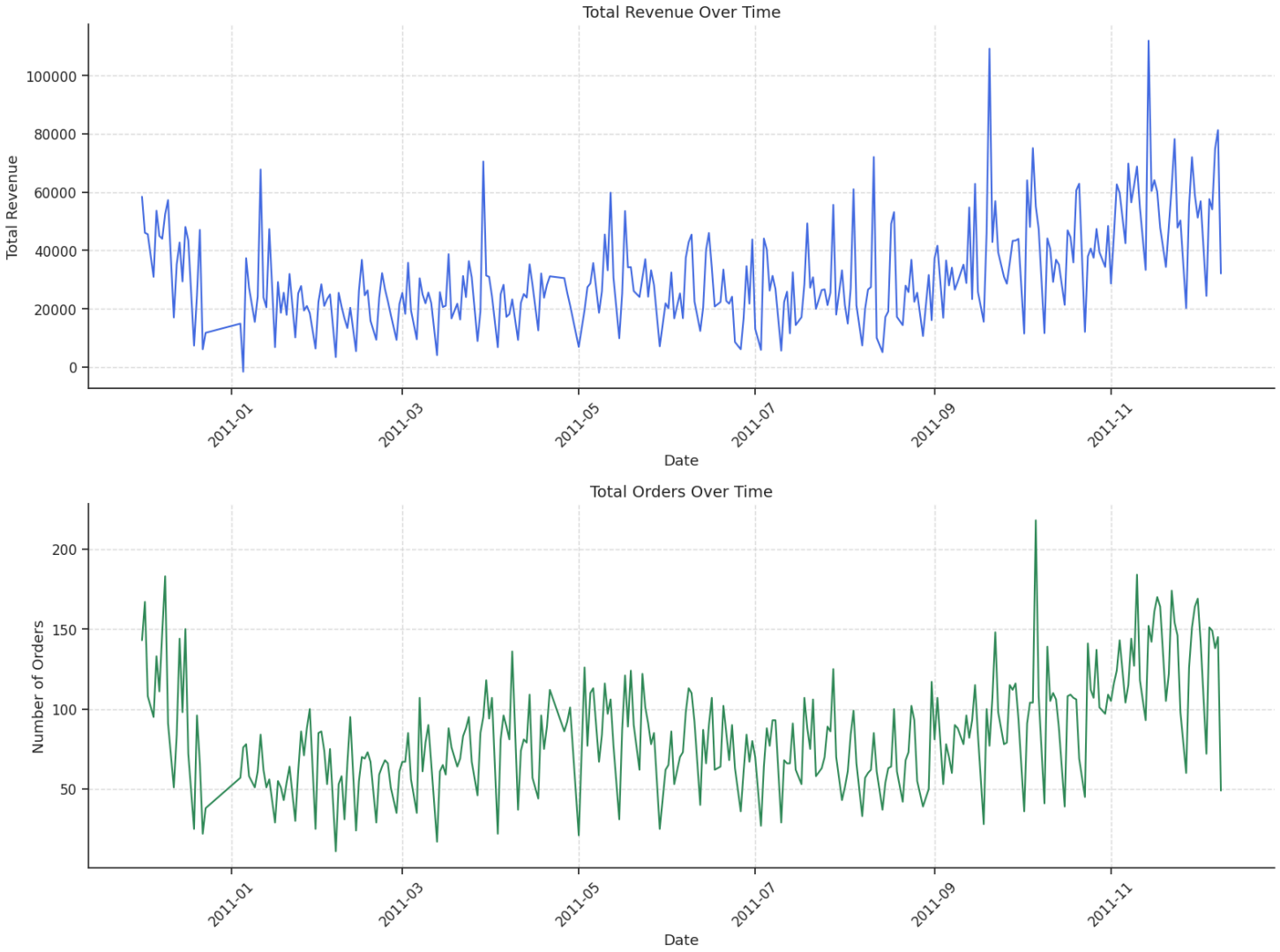
```
Total Revenue: 9726003.054003103

Total Orders: 25900

Average Order value: 375.5213534364132
```

Sales trend over time

In [26]:
```
# Monthly Trend Data
monthly_trend = business_df.groupby('InvoiceDate').agg(
    Orders=('InvoiceNo', 'nunique'),
    Revenue=('TotalPrice', 'sum')
).reset_index()

# Sort by date to ensure the plot is in chronological order
monthly_trend = monthly_trend.sort_values('InvoiceDate')
```

In [27]:

```
fig, axes = plt.subplots(2, 1, figsize=(16, 12))

# Plot 1: Total Revenue (on the left subplot, axes[0])
axes[0].plot(monthly_trend['InvoiceDate'], monthly_trend['Revenue'], color='royalblue')
axes[0].set_title('Total Revenue Over Time', fontsize=14)
axes[0].set_xlabel('Date')
axes[0].set_ylabel('Total Revenue')
axes[0].tick_params(axis='x', rotation=45)
axes[0].grid(True, linestyle='--', alpha=0.6)

# Plot 2: Number of Unique Invoices (on the right subplot, axes[1])
axes[1].plot(monthly_trend['InvoiceDate'], monthly_trend['Orders'], color='seagreen')
axes[1].set_title('Total Orders Over Time', fontsize=14)
axes[1].set_xlabel('Date')
axes[1].set_ylabel('Number of Orders')
axes[1].tick_params(axis='x', rotation=45)
axes[1].grid(True, linestyle='--', alpha=0.6)

# Adjust layout to prevent labels from overlapping
plt.tight_layout()
# Save Plot
plt.savefig('revenue_and_invoices_side_by_side.png')
```



In [28]:

```
# 1. Filter the DataFrame for the specific year and month
december_2011_df = business_df[
    (business_df['InvoiceDate'].dt.year == 2011) &
    (business_df['InvoiceDate'].dt.month == 12)
]

# 2. Find the latest date in that month
if not december_2011_df.empty:
    last_date = december_2011_df['InvoiceDate'].max()
    print(f"The last recorded transaction date in December 2011 is: {last_date.date()}")

    # 3. Interpret the result
    if last_date.day < 31:
        print("\nConclusion: The data for December 2011 appears to be incomplete.")
    else:
        print("\nConclusion: The data for December 2011 runs to the end of the month.")
else:
    print("No data found for December 2011.")
```

```
The last recorded transaction date in December 2011 is: 2011-12-09

Conclusion: The data for December 2011 appears to be incomplete.
```

Major Autumn Spike May Be due to Holiday Shopping Season, while the drop in Dec 2011 is due to incomplete data

How is the business performing geographically

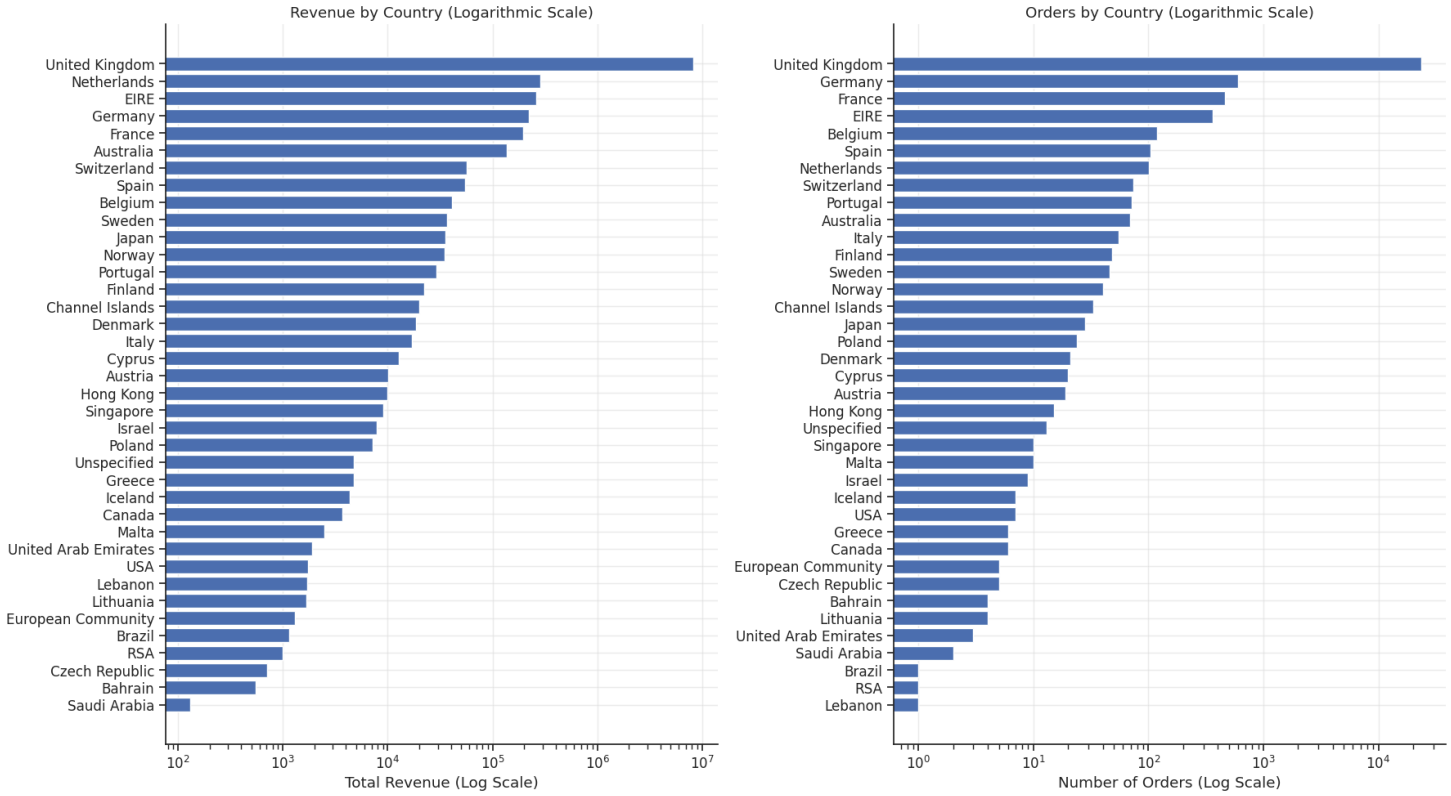
In [29]:

```
country_spread = business_df.groupby('Country').agg(
    Orders=('InvoiceNo', 'nunique'),
    Revenue=('TotalPrice', 'sum')
).reset_index()
country_spread = country_spread.sort_values('Revenue',ascending=False)
print(country_spread)
```

	Country	Orders	Revenue
36	United Kingdom	23494	8167124.284
24	Netherlands	101	284661.540
10	EIRE	360	262993.380
14	Germany	603	221509.470
13	France	461	197317.110
0	Australia	69	137009.770
33	Switzerland	74	56363.050
31	Spain	105	54756.030
3	Belgium	119	40910.960
32	Sweden	46	36585.410
20	Japan	28	35340.620
25	Norway	40	35163.460
27	Portugal	71	29302.970
12	Finland	48	22326.740
6	Channel Islands	33	20076.390
9	Denmark	21	18768.140
19	Italy	55	16890.510
7	Cyprus	20	12858.760
1	Austria	19	10154.320
16	Hong Kong	15	9908.240
30	Singapore	10	9120.390
18	Israel	9	7901.970
26	Poland	24	7213.140
37	Unspecified	13	4740.940
15	Greece	6	4710.520
17	Iceland	7	4310.000
5	Canada	6	3666.380
23	Malta	10	2505.470
35	United Arab Emirates	3	1902.280
34	USA	7	1730.920
21	Lebanon	1	1693.880
22	Lithuania	4	1661.060
11	European Community	5	1291.750
4	Brazil	1	1143.600
28	RSA	1	1002.310
8	Czech Republic	5	707.720
2	Bahrain	4	548.400
29	Saudi Arabia	2	131.170

In [30]:

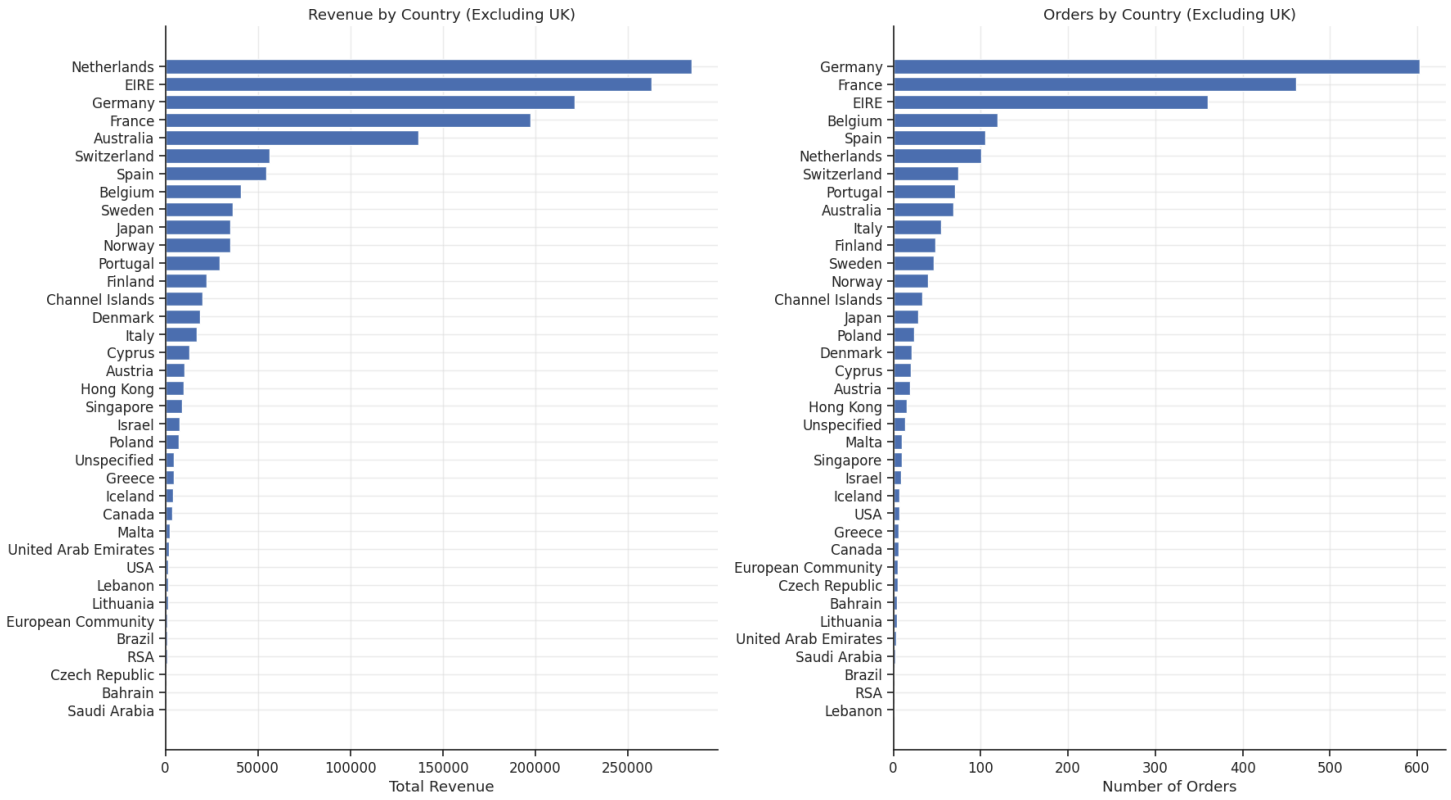
```
fig_all, axes_all = plt.subplots(1, 2, figsize=(18, 10))

# Left subplot: Revenue
df_rev_all = country_spread.sort_values('Revenue', ascending=True)
axes_all[0].barh(df_rev_all['Country'], df_rev_all['Revenue'])
axes_all[0].set_xscale('log') # Use a logarithmic scale
axes_all[0].set_title('Revenue by Country (Logarithmic Scale)')
axes_all[0].set_xlabel('Total Revenue (Log Scale)')

# Right subplot: Orders
df_ord_all = country_spread.sort_values('Orders', ascending=True)
axes_all[1].barh(df_ord_all['Country'], df_ord_all['Orders'])
axes_all[1].set_xscale('log') # Use a logarithmic scale
axes_all[1].set_title('Orders by Country (Logarithmic Scale)')
axes_all[1].set_xlabel('Number of Orders (Log Scale)')

plt.tight_layout()
plt.savefig('charts_including_uk_log_scale.png')
```



The UK accounts for over 80%of the total revenue,and has more than 50 times the number of orders compared to the next leading country

In [31]:

```
df_no_uk = country_spread[country_spread['Country'] != 'United Kingdom']

# Create a figure with two subplots side-by-side
fig, axes = plt.subplots(1, 2, figsize=(18, 10))

# Left subplot: Revenue
df_revenue = df_no_uk.sort_values('Revenue', ascending=True)
axes[0].barh(df_revenue['Country'], df_revenue['Revenue'])
axes[0].set_title('Revenue by Country (Excluding UK)')
axes[0].set_xlabel('Total Revenue')

# Right subplot: Orders
df_orders = df_no_uk.sort_values('Orders', ascending=True)
axes[1].barh(df_orders['Country'], df_orders['Orders'])
axes[1].set_title('Orders by Country (Excluding UK)')
axes[1].set_xlabel('Number of Orders')

plt.tight_layout()
plt.savefig('charts_excluding_uk.png')
```



While Germany has 6 times the number of orders of Netherlands, The Netherlands Has Revenue 30%Higher than Germany

Who are our most valuable customers

Recency, Frequency, Monetary

In [32]:
```
customer_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 377176 entries, 0 to 541908
Data columns (total 13 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    377176 non-null  object        
 1   StockCode    377176 non-null  object        
 2   Description  377176 non-null  object        
 3   Quantity     377176 non-null  int64         
 4   InvoiceDate  377176 non-null  datetime64[ns]
 5   UnitPrice    377176 non-null  float64       
 6   CustomerID   377176 non-null  object        
 7   Country      377176 non-null  object        
 8   Hour         377176 non-null  int32         
 9   Year         377176 non-null  int32         
 10  Month        377176 non-null  int32         
 11  Day_Name     377176 non-null  object        
 12  TotalPrice   377176 non-null  float64       
dtypes: datetime64[ns](1), float64(2), int32(3), int64(1), object(6)
memory usage: 36.0+ MB
```

In [33]:
```
snapshot_date = pd.to_datetime('2011-12-10')

RFM = customer_df.groupby('CustomerID').agg(
    Recency=('InvoiceDate','max'),
    Frequency=('InvoiceNo','nunique'),
    Revenue=('TotalPrice','sum')
).reset_index()
RFM['AOV'] = round(RFM['Revenue']/RFM['Frequency'],2)
RFM['Recency'] = (snapshot_date - RFM['Recency']).dt.days


print(RFM.head())
```

```
   CustomerID  Recency  Frequency  Revenue      AOV
0     12347.0        3          7  4060.40   580.06
1     12348.0      249          3   200.60    66.87
2     12349.0       19          1  1417.60  1417.60
3     12350.0      311          1   294.40   294.40
4     12352.0       37          7  1365.94   195.13
```

In [34]:
```
# Create labels and assign scores from 1 to 5
r_labels = range(5, 0, -1) # Lower recency (more recent) gets a higher score
f_labels = range(1, 5)
m_labels = range(1, 6)

# Create RFM scores based on quintiles
RFM['R_score'] = pd.qcut(RFM['Recency'], q=5, labels=r_labels, duplicates='drop').astype(int)
RFM['F_score'] = pd.qcut(RFM['Frequency'], q=5, labels=f_labels, duplicates='drop').astype(int)
RFM['M_score'] = pd.qcut(RFM['Revenue'], q=5, labels=m_labels, duplicates='drop').astype(int)

# Combine the scores into a single RFM score
RFM['RFM_Score'] = RFM['R_score'].astype(str) + RFM['F_score'].astype(str) + RFM['M_score'].astype(str)
```

In [35]:

```
# Create a dictionary to map scores to segment names
segment_map = {
    r'[4-5][4-5][4-5]': 'Champions',
    r'[3-5][3-5][1-5]': 'Loyal Customers',
    r'[4-5][1-2][1-5]': 'Recent Customers',
    r'[2-3][1-3][1-5]': 'Potential Loyalists',
    r'[1-3][3-5][1-5]': 'At-Risk Customers',
    r'[1-2][1-2][1-5]': 'Needs Attention',
    r'[1-2][1-5][4-5]': 'Big Spenders'
}

# Create a new 'Segment' column
RFM['Segment'] = RFM['RFM_Score'].replace(segment_map, regex=True)
```

In [36]:

```
segment_analysis = RFM.groupby('Segment').agg(
    Avg_Recency=('Recency', 'mean'),
    Avg_Frequency=('Frequency', 'mean'),
    Avg_Revenue=('Revenue', 'mean'),
    Customer_Count=('CustomerID', 'count')
).round(1).sort_values(by='Customer_Count', ascending=False).reset_index()

segment_analysis
```

Out[36]:

	Segment	Avg_Recency	Avg_Frequency	Avg_Revenue	Customer_Count
0	Potential Loyalists	89.2	1.9	638.4	1388
1	Needs Attention	269.7	1.3	356.0	816
2	Recent Customers	17.7	1.9	588.8	717
3	Champions	12.1	13.6	5029.2	643
4	Loyal Customers	30.2	5.2	1733.8	617
5	At-Risk Customers	164.4	7.3	1719.3	79

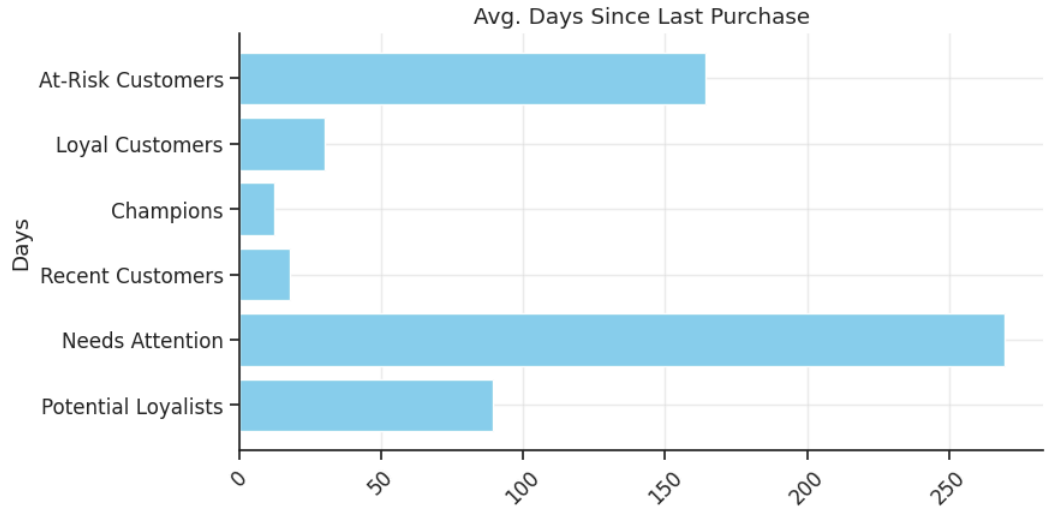
In [37]:

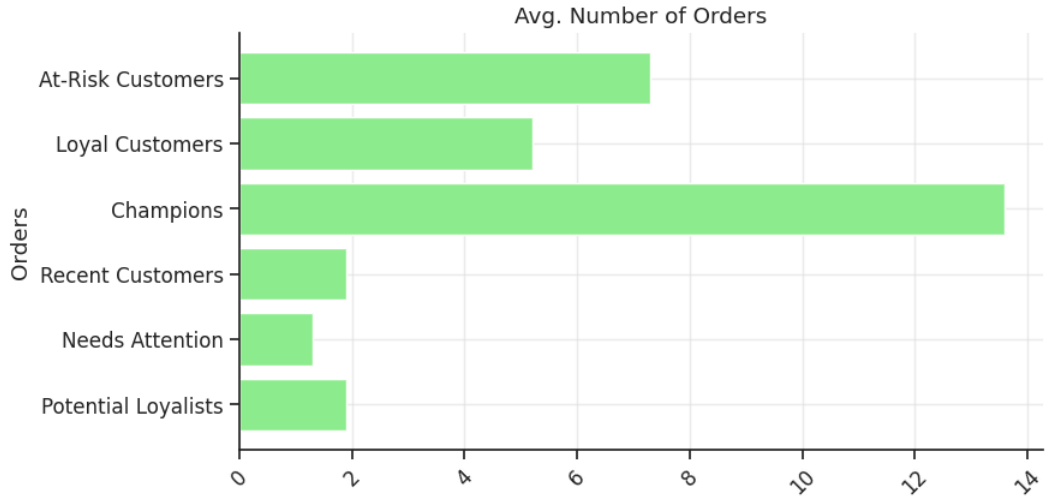
```
print(segment_analysis)
```

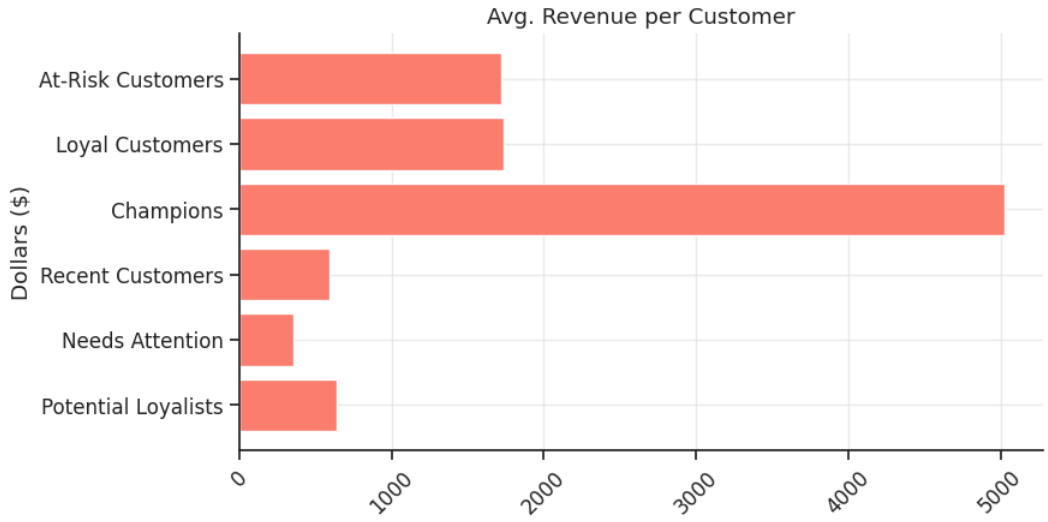
```
              Segment  Avg_Recency  Avg_Frequency  Avg_Revenue  \
0  Potential Loyalists         89.2            1.9        638.4
1      Needs Attention        269.7            1.3        356.0
2     Recent Customers         17.7            1.9        588.8
3            Champions         12.1           13.6       5029.2
4      Loyal Customers         30.2            5.2       1733.8
5    At-Risk Customers        164.4            7.3       1719.3

   Customer_Count
0            1388
1             816
2             717
3             643
4             617
5              79
```

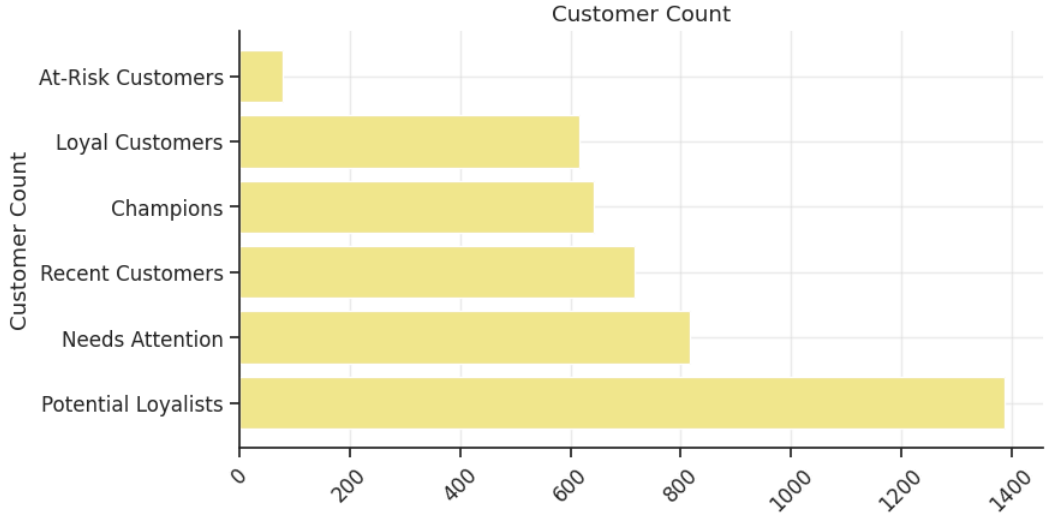
In [38]:

```
fig, (ax1, ax2, ax3,ax4) = plt.subplots(4, 1, figsize=(9, 18))

# Plot 1: Average Recency
ax1.barh(segment_analysis['Segment'], segment_analysis['Avg_Recency'], color='skyblue')
ax1.set_title('Avg. Days Since Last Purchase')
ax1.tick_params(axis='x', rotation=45)
ax1.set_ylabel('Days')

# Plot 2: Average Frequency
ax2.barh(segment_analysis['Segment'], segment_analysis['Avg_Frequency'], color='lightgreen')
ax2.set_title('Avg. Number of Orders')
ax2.tick_params(axis='x', rotation=45)
ax2.set_ylabel('Orders')

# Plot 3: Average Revenue
ax3.barh(segment_analysis['Segment'], segment_analysis['Avg_Revenue'], color='salmon')
ax3.set_title('Avg. Revenue per Customer')
ax3.tick_params(axis='x', rotation=45)
ax3.set_ylabel('Dollars ($)')

# Plot 4: Total Customers
ax4.barh(segment_analysis['Segment'], segment_analysis['Customer_Count'], color='khaki')
ax4.set_title('Customer Count')
ax4.tick_params(axis='x', rotation=45)
ax4.set_ylabel('Customer Count')

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


Avg. Days Since Last Purchase
Days
At-Risk Customers
Loyal Customers
Champions
Recent Customers
Needs Attention
Potential Loyalists
0
50
100
150
200
250


Avg. Number of Orders
Orders
At-Risk Customers
Loyal Customers
Champions
Recent Customers
Needs Attention
Potential Loyalists
0
2
4
6
8
10
12
14


Avg. Revenue per Customer
Dollars ($)
At-Risk Customers
Loyal Customers
Champions
Recent Customers
Needs Attention
Potential Loyalists
0
1000
2000
3000
4000
5000


Customer Count
Customer Count
At-Risk Customers
Loyal Customers
Champions
Recent Customers
Needs Attention
Potential Loyalists
0
200
400
600
800
1000
1200
1400

retaining customers

Cohort Analysis

In [39]:
```
# Create Nedded Columns
customer_df['year_month'] = df['InvoiceDate'].dt.to_period('M')

customer_df['CohortMonth'] = customer_df.groupby('CustomerID')['year_month'].transform('min')
# -----
invoice_month = customer_df['InvoiceDate'].dt.year * 12 + customer_df['InvoiceDate'].dt.month
cohort_month = customer_df['CohortMonth'].dt.year * 12 + customer_df['CohortMonth'].dt.month

customer_df['CohortIndex']=  invoice_month - cohort_month
```

In [40]:
```
# Group by cohort month and index, then count unique customers
cohort_data = customer_df.groupby(['CohortMonth', 'CohortIndex'])['CustomerID'].nunique()

# Create the pivot table (cohort table)
cohort_counts = cohort_data.unstack(level=1)
cohort_counts
```

Out[40]:

CohortIndex	0	1	2	3	4	5	6	7	8	9	10	11	12
CohortMonth													
2010-12	856.0	311.0	274.0	320.0	306.0	345.0	308.0	294.0	294.0	330.0	315.0	430.0	223.0
2011-01	407.0	88.0	113.0	91.0	129.0	116.0	100.0	99.0	124.0	133.0	147.0	48.0	NaN
2011-02	367.0	68.0	71.0	104.0	101.0	90.0	92.0	99.0	93.0	115.0	25.0	NaN	NaN
2011-03	450.0	66.0	109.0	90.0	103.0	76.0	119.0	104.0	121.0	38.0	NaN	NaN	NaN
2011-04	293.0	63.0	60.0	60.0	56.0	69.0	65.0	74.0	21.0	NaN	NaN	NaN	NaN
2011-05	279.0	57.0	50.0	49.0	59.0	66.0	74.0	27.0	NaN	NaN	NaN	NaN	NaN
2011-06	234.0	40.0	35.0	62.0	53.0	77.0	23.0	NaN	NaN	NaN	NaN	NaN	NaN
2011-07	192.0	33.0	42.0	45.0	52.0	23.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08	168.0	31.0	40.0	41.0	22.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09	295.0	70.0	90.0	34.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10	358.0	87.0	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11	320.0	36.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

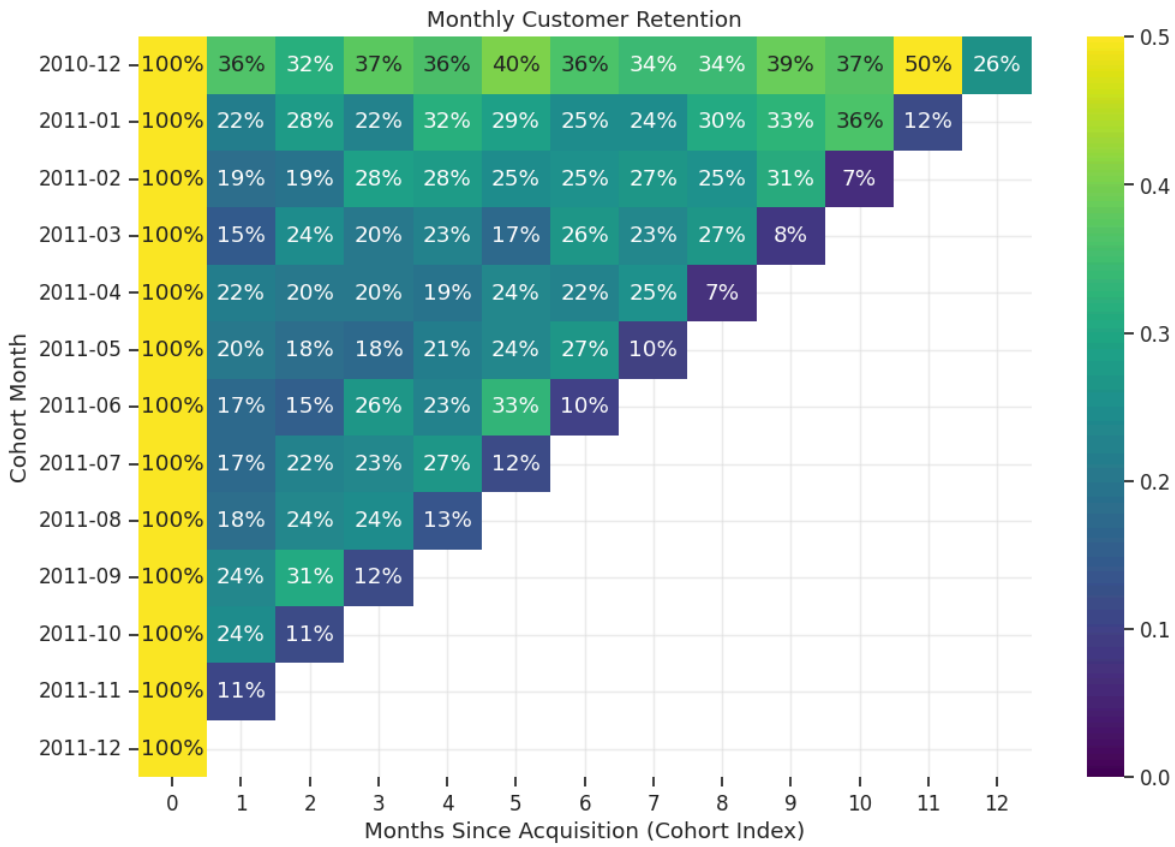
In [41]:
```
# Get the initial size of each cohort (the first column)
cohort_size = cohort_counts.iloc[:, 0]

# Divide the counts by the cohort size to get the retention rate
retention = cohort_counts.div(cohort_size, axis=0)
retention.index = retention.index.strftime('%Y-%m')

retention
```

Out[41]:

CohortIndex	0	1	2	3	4	5	6	7	8	9	10	11	12
CohortMonth													
2010-12	1.0	0.363318	0.320093	0.373832	0.357477	0.403037	0.359813	0.343458	0.343458	0.385514	0.367991	0.502336	0.260514
2011-01	1.0	0.216216	0.277641	0.223587	0.316953	0.285012	0.245700	0.243243	0.304668	0.326781	0.361179	0.117936	NaN
2011-02	1.0	0.185286	0.193460	0.283379	0.275204	0.245232	0.250681	0.269755	0.253406	0.313351	0.068120	NaN	NaN
2011-03	1.0	0.146667	0.242222	0.200000	0.228889	0.168889	0.264444	0.231111	0.268889	0.084444	NaN	NaN	NaN
2011-04	1.0	0.215017	0.204778	0.204778	0.191126	0.235495	0.221843	0.252560	0.071672	NaN	NaN	NaN	NaN
2011-05	1.0	0.204301	0.179211	0.175627	0.211470	0.236559	0.265233	0.096774	NaN	NaN	NaN	NaN	NaN
2011-06	1.0	0.170940	0.149573	0.264957	0.226496	0.329060	0.098291	NaN	NaN	NaN	NaN	NaN	NaN
2011-07	1.0	0.171875	0.218750	0.234375	0.270833	0.119792	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08	1.0	0.184524	0.238095	0.244048	0.130952	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09	1.0	0.237288	0.305085	0.115254	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10	1.0	0.243017	0.114525	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11	1.0	0.112500	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [42]:

```
# Heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(
    retention,
    annot=True,
    fmt='.0%',
    cmap='viridis',
    vmin=0.0,
    vmax=0.5    )
plt.title('Monthly Customer Retention')
plt.ylabel('Cohort Month')
plt.xlabel('Months Since Acquisition (Cohort Index)')
plt.savefig('Cohort_heatmap.png')
plt.show()
```



Cutomser Who Made Their First Purchase on 2010-12 showed the highest retention %over the year with a spike 50%on november may indicate succesful holiday season

When do customers shop?

In [43]:

```
weekdays = customer_df.groupby('Day_Name').agg(
    total_orders = ('InvoiceNo','nunique'),
    revenue = ('TotalPrice','sum')
).reset_index()
weekdays
```

Out[43]:

	Day_Name	total_orders	revenue
0	Friday	2669	909306.151
1	Monday	2709	968931.601
2	Sunday	2140	676505.411
3	Thursday	3848	1320793.480
4	Tuesday	2999	1055463.551
5	Wednesday	3266	1107107.180

In [44]:

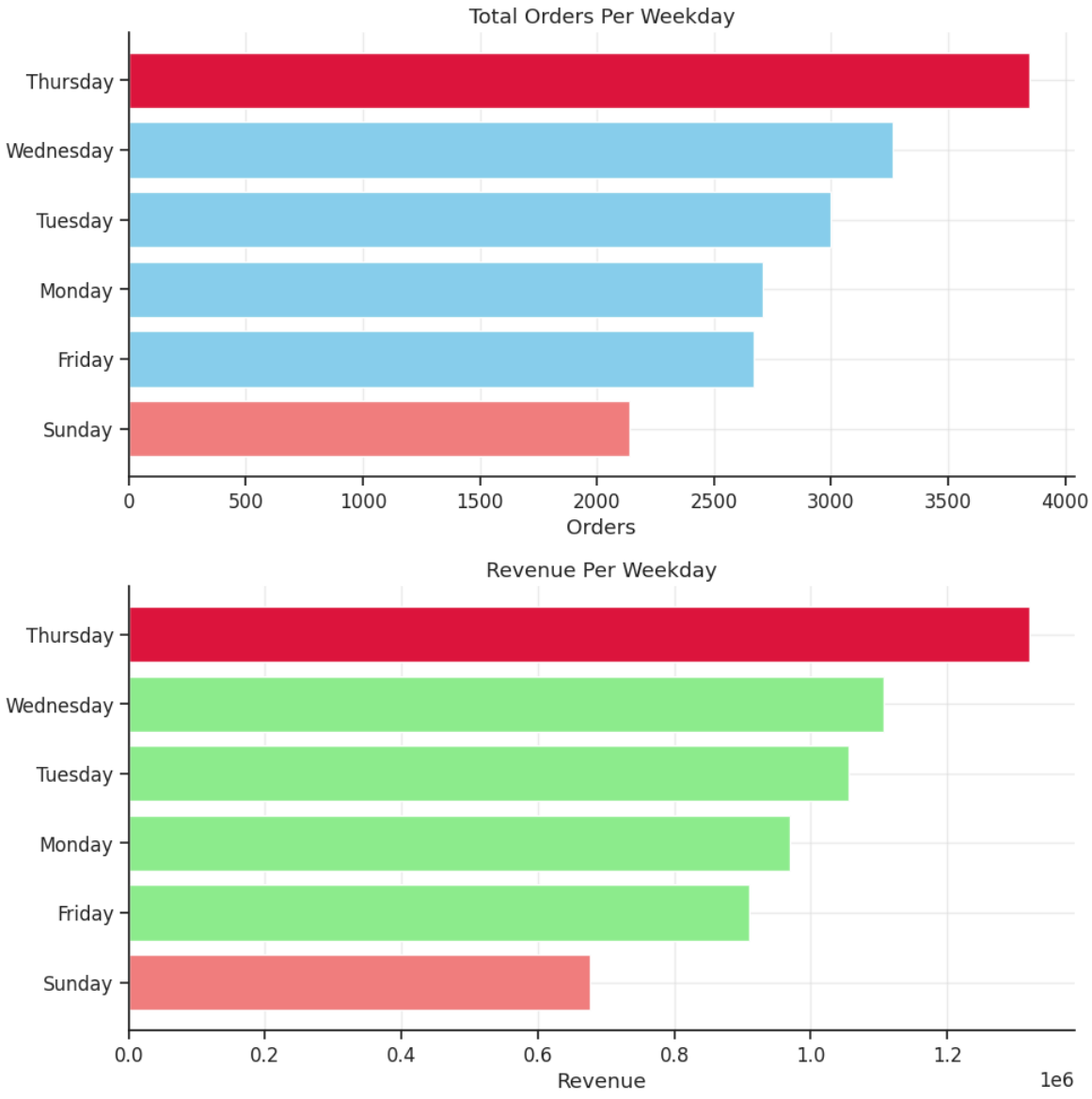
```
weekdays['orders_pct'] = round((weekdays['total_orders'] / sum(weekdays['total_orders'])),4)
weekdays['revenue_pct'] = round((weekdays['revenue'] / sum(weekdays['revenue'])),4)
weekdays
```

Out[44]:

	Day_Name	total_orders	revenue	orders_pct	revenue_pct
0	Friday	2669	909306.151	0.1514	0.1506
1	Monday	2709	968931.601	0.1536	0.1605
2	Sunday	2140	676505.411	0.1214	0.1120
3	Thursday	3848	1320793.480	0.2183	0.2187
4	Tuesday	2999	1055463.551	0.1701	0.1748
5	Wednesday	3266	1107107.180	0.1852	0.1834

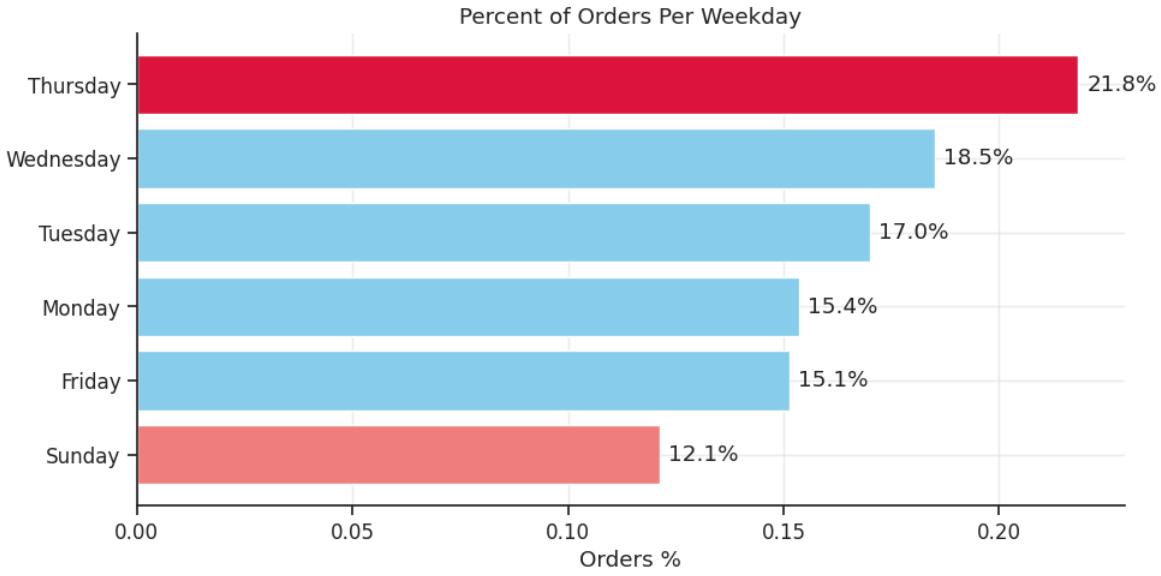
In [45]:

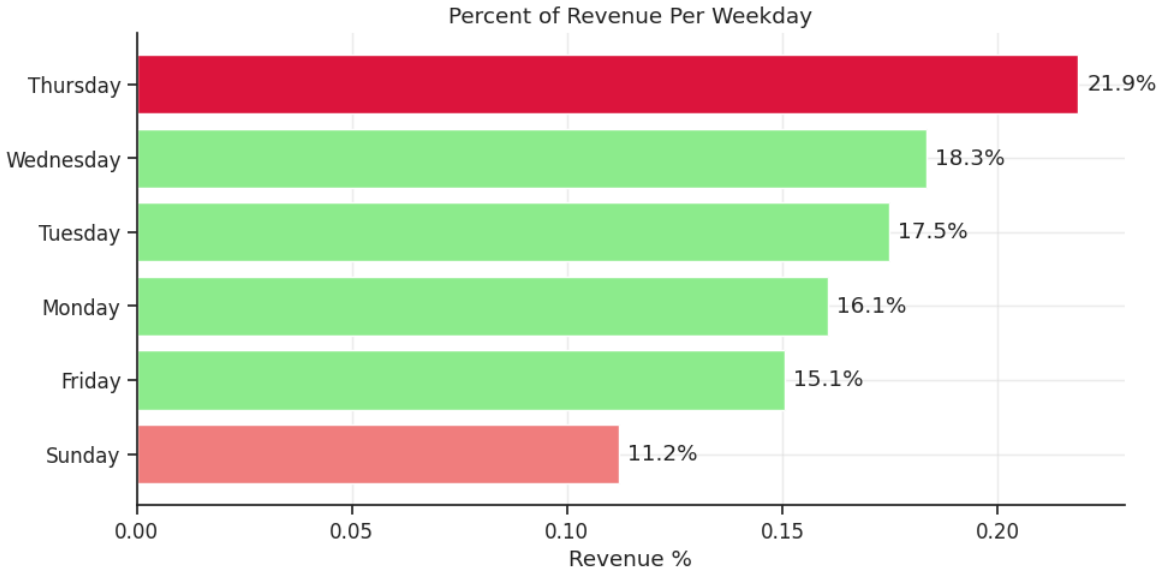
```
# 1. Sort the data for each plot
orders_sorted = weekdays.sort_values('total_orders', ascending=True)
revenue_sorted = weekdays.sort_values('revenue', ascending=True)

# 2. Create color lists to highlight the max and min values
orders_colors = ['crimson' if x == orders_sorted['total_orders'].max() else 'lightcoral' if x == orders_sorted['total_orders'].min() else 'skyblue' fo
r x in orders_sorted['total_orders']]
revenue_colors = ['crimson' if x == revenue_sorted['revenue'].max() else 'lightcoral' if x == revenue_sorted['revenue'].min() else 'lightgreen' for x
in revenue_sorted['revenue']]

# 3. Create the subplots
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(10, 10))

# Plot 1: Total Orders
ax1.barh(orders_sorted['Day_Name'], orders_sorted['total_orders'], color=orders_colors)
ax1.set_title('Total Orders Per Weekday')
ax1.set_xlabel('Orders')

# Plot 2: Revenue
ax2.barh(revenue_sorted['Day_Name'], revenue_sorted['revenue'], color=revenue_colors)
ax2.set_title('Revenue Per Weekday')
ax2.set_xlabel('Revenue')

plt.tight_layout()
plt.savefig('Weekday_Bar.png')
plt.show()
```



In [46]:

```
# 1. Sort the data for each plot
orders_sorted = weekdays.sort_values('orders_pct', ascending=True)
revenue_sorted = weekdays.sort_values('revenue_pct', ascending=True)

# 2. Create color lists to highlight the max and min values
orders_colors = ['crimson' if x == orders_sorted['orders_pct'].max() else 'lightcoral' if x == orders_sorted['orders_pct'].min() else 'skyblue' for x
in orders_sorted['orders_pct']]
revenue_colors = ['crimson' if x == revenue_sorted['revenue_pct'].max() else 'lightcoral' if x == revenue_sorted['revenue_pct'].min() else 'lightgree
n' for x in revenue_sorted['revenue_pct']]

# 3. Create the subplots
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(10, 10))

# Plot 1: Total Orders
bars1 = ax1.barh(orders_sorted['Day_Name'], orders_sorted['orders_pct'], color=orders_colors)
ax1.set_title('Percent of Orders Per Weekday')
ax1.set_xlabel('Orders %')

# --- Add labels to the bars for Plot 1 ---
for bar in bars1:
    width = bar.get_width()
    ax1.text(width + 0.002,  # x-position
             bar.get_y() + bar.get_height() / 2,  # y-position
             f'{width:.1%}',  # The label text, formatted as a percentage
             va='center')

# Plot 2: Revenue
bars2 = ax2.barh(revenue_sorted['Day_Name'], revenue_sorted['revenue_pct'], color=revenue_colors)
ax2.set_title('Percent of Revenue Per Weekday')
ax2.set_xlabel('Revenue %')

# --- Add labels to the bars for Plot 2 ---
for bar in bars2:
    width = bar.get_width()
    ax2.text(width + 0.002,  # x-position
             bar.get_y() + bar.get_height() / 2,  # y-position
             f'{width:.001%}',  # The label text, formatted as a percentage
             va='center')

plt.tight_layout()
plt.savefig('Weekday_pct_Bar.png')
plt.show()
```





Thursday is unequivocally the most important day with 21.8% of total orders and 21.9% of revenue

the entire mid-week period from Monday to Thursday forms a strong and consistent block of high sales activity with 52% of revenue and 51% of total orders.

Sunday being the weakest day by a considerable margin with only 11.2% of revenue and 12.1% of total orders

In [47]:

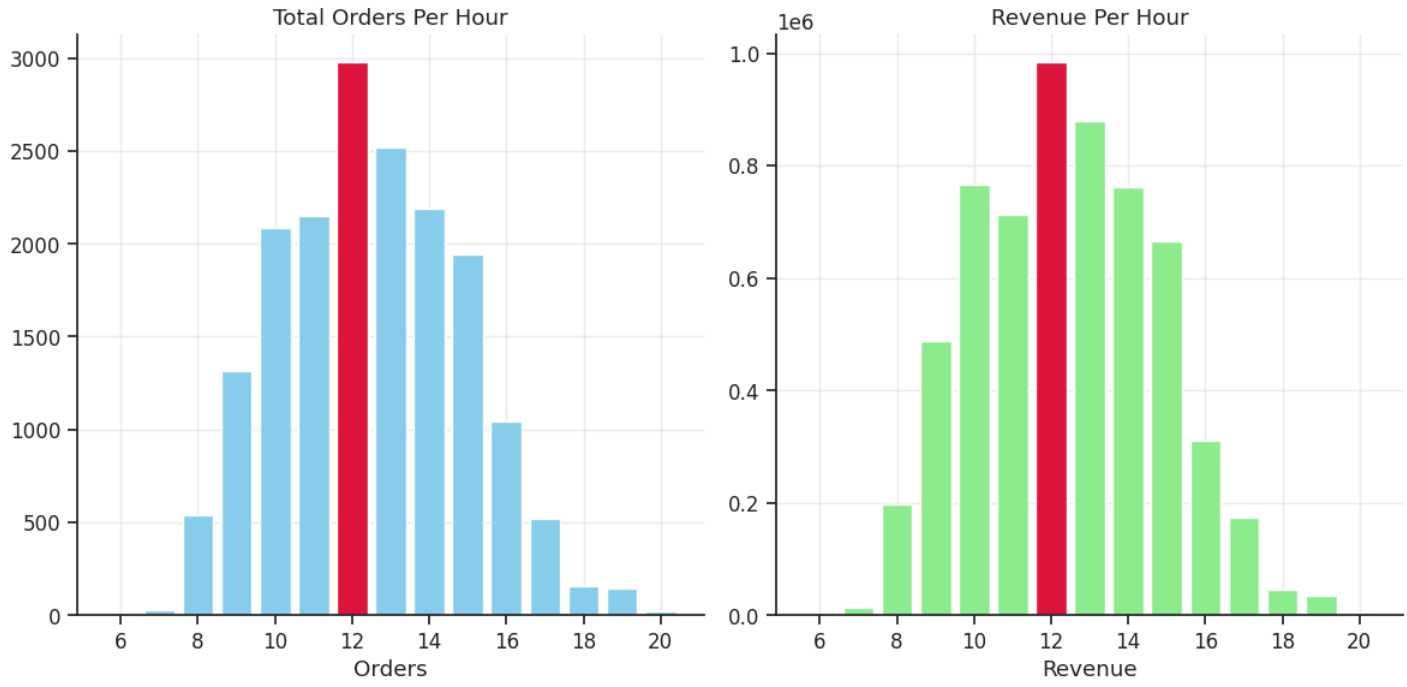
```
hour_rush = customer_df.groupby('Hour').agg(
    total_orders = ('InvoiceNo','nunique'),
    revenue = ('TotalPrice','sum')
).reset_index()
hour_rush['orders_pct'] = round((hour_rush['total_orders'] / sum(hour_rush['total_orders'])),4)
hour_rush['revenue_pct'] = round((hour_rush['revenue'] / sum(hour_rush['revenue'])),4)
hour_rush
```

Out[47]:

	Hour	total_orders	revenue	orders_pct	revenue_pct
0	6	1	4.250	0.0001	0.0000
1	7	26	14015.640	0.0015	0.0023
2	8	536	197408.230	0.0304	0.0327
3	9	1313	487266.221	0.0745	0.0807
4	10	2084	764945.351	0.1182	0.1267
5	11	2152	713232.590	0.1221	0.1181
6	12	2979	984121.130	0.1690	0.1630
7	13	2520	878350.900	0.1429	0.1455
8	14	2192	761453.261	0.1243	0.1261
9	15	1945	665031.770	0.1103	0.1101
10	16	1046	311496.990	0.0593	0.0516
11	17	522	174053.191	0.0296	0.0288
12	18	157	45444.930	0.0089	0.0075
13	19	141	35808.940	0.0080	0.0059
14	20	18	5473.980	0.0010	0.0009

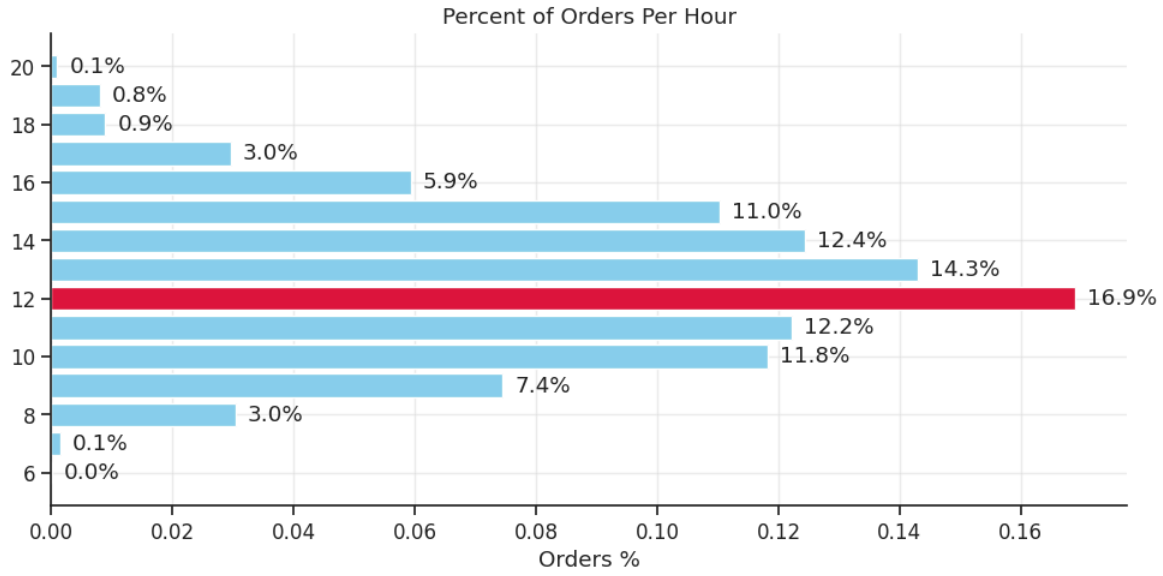
In [48]:

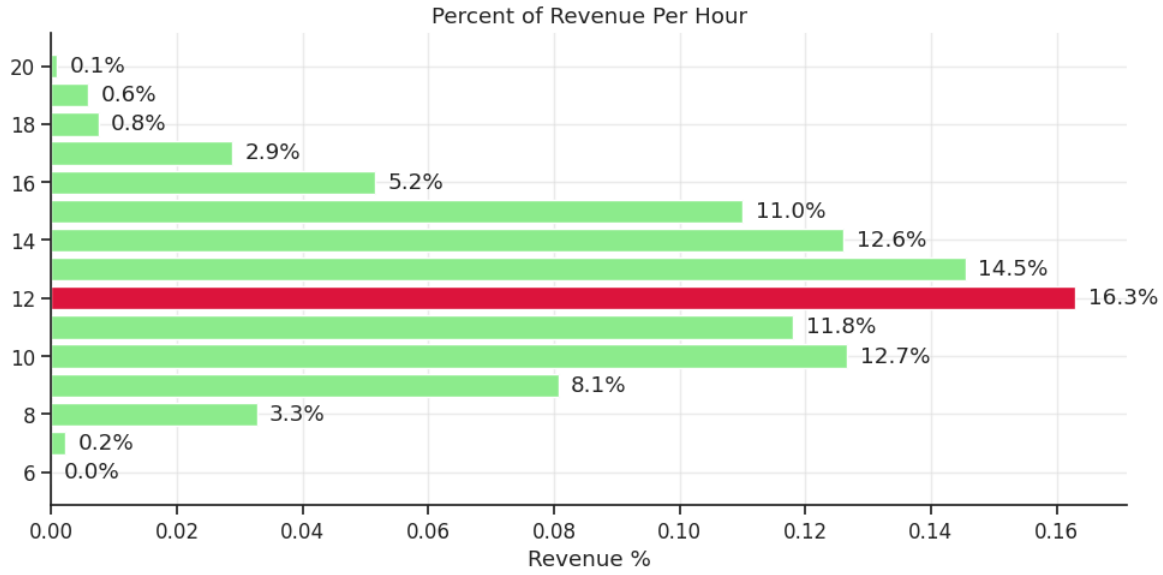
```
# 1. Sort the data for each plot
orders_sorted = hour_rush.sort_values('total_orders', ascending=True)
revenue_sorted = hour_rush.sort_values('revenue', ascending=True)

# 2. Create color lists to highlight the max and min values
orders_colors = ['crimson' if x == orders_sorted['total_orders'].max() else 'lightcoral' if x == orders_sorted['total_orders'].min() else 'skyblue' fo
r x in orders_sorted['total_orders']]
revenue_colors = ['crimson' if x == revenue_sorted['revenue'].max() else 'lightcoral' if x == revenue_sorted['revenue'].min() else 'lightgreen' for x
in revenue_sorted['revenue']]

# 3. Create the subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

# Plot 1: Total Orders
ax1.bar(orders_sorted['Hour'], orders_sorted['total_orders'], color=orders_colors)
ax1.set_title('Total Orders Per Hour')
ax1.set_xlabel('Orders')

# Plot 2: Revenue
ax2.bar(revenue_sorted['Hour'], revenue_sorted['revenue'], color=revenue_colors)
ax2.set_title('Revenue Per Hour')
ax2.set_xlabel('Revenue')

plt.tight_layout()
plt.savefig('Hour_Bar.png')
plt.show()
```



In [49]:

```
# 1. Sort the data for each plot
orders_sorted = hour_rush.sort_values('orders_pct', ascending=True)
revenue_sorted = hour_rush.sort_values('revenue_pct', ascending=True)

# 2. Create color lists to highlight the max and min values
orders_colors = ['crimson' if x == orders_sorted['orders_pct'].max() else 'lightcoral' if x == orders_sorted['orders_pct'].min() else 'skyblue' for x
in orders_sorted['orders_pct']]
revenue_colors = ['crimson' if x == revenue_sorted['revenue_pct'].max() else 'lightcoral' if x == revenue_sorted['revenue_pct'].min() else 'lightgree
n' for x in revenue_sorted['revenue_pct']]

# 3. Create the subplots
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(10, 10))

# Plot 1: Total Orders
bars1 = ax1.barh(orders_sorted['Hour'], orders_sorted['orders_pct'], color=orders_colors)
ax1.set_title('Percent of Orders Per Hour')
ax1.set_xlabel('Orders %')

# --- Add labels to the bars for Plot 1 ---
for bar in bars1:
    width = bar.get_width()
    ax1.text(width + 0.002,  # x-position
             bar.get_y() + bar.get_height() / 2,  # y-position
             f'{width:.1%}',  # The label text, formatted as a percentage
             va='center')

# Plot 2: Revenue
bars2 = ax2.barh(revenue_sorted['Hour'], revenue_sorted['revenue_pct'], color=revenue_colors)
ax2.set_title('Percent of Revenue Per Hour')
ax2.set_xlabel('Revenue %')

# --- Add labels to the bars for Plot 2 ---
for bar in bars2:
    width = bar.get_width()
    ax2.text(width + 0.002,  # x-position
             bar.get_y() + bar.get_height() / 2,  # y-position
             f'{width:.001%}',  # The label text, formatted as a percentage
             va='center')

plt.tight_layout()
plt.savefig('Hour_pct_Bar.png')
plt.show()
```





12pm has the highest contribution to revenue with 16.3%and 16.9%of total orders

From 10am to 3pm Has the highest contribution with 78.6%of total order and 79%of revenue which indicate a high demand in mid-day

In [50]:
```
customer_df.columns
```

Out[50]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'Hour', 'Year', 'Month',
       'Day_Name', 'TotalPrice', 'year_month', 'CohortMonth', 'CohortIndex'],
      dtype='object')
```

best and worst-selling products

In [51]:
```
products = customer_df.groupby('Description').agg(
    orders=('Quantity', 'sum'),
    sales=('TotalPrice', 'sum'),
    avg_unit_price=('UnitPrice', 'mean')  # Use 'mean' to get the average price
).reset_index().sort_values(by='sales', ascending=False)

products.head()
```

Out[51]:

	Description	orders	sales	avg_unit_price
2715	REGENCY CAKESTAND 3 TIER	10035	116442.55	12.426099
3626	WHITE HANGING HEART T-LIGHT HOLDER	21921	60187.91	2.898833
2301	PARTY BUNTING	11489	53226.73	4.894598
215	ASSORTED COLOUR BIRD ORNAMENT	20351	34381.67	1.689819
1728	JUMBO BAG RED RETROSPOT	15098	30807.00	2.054418

In [52]:
```
orders_sorted.head()
```

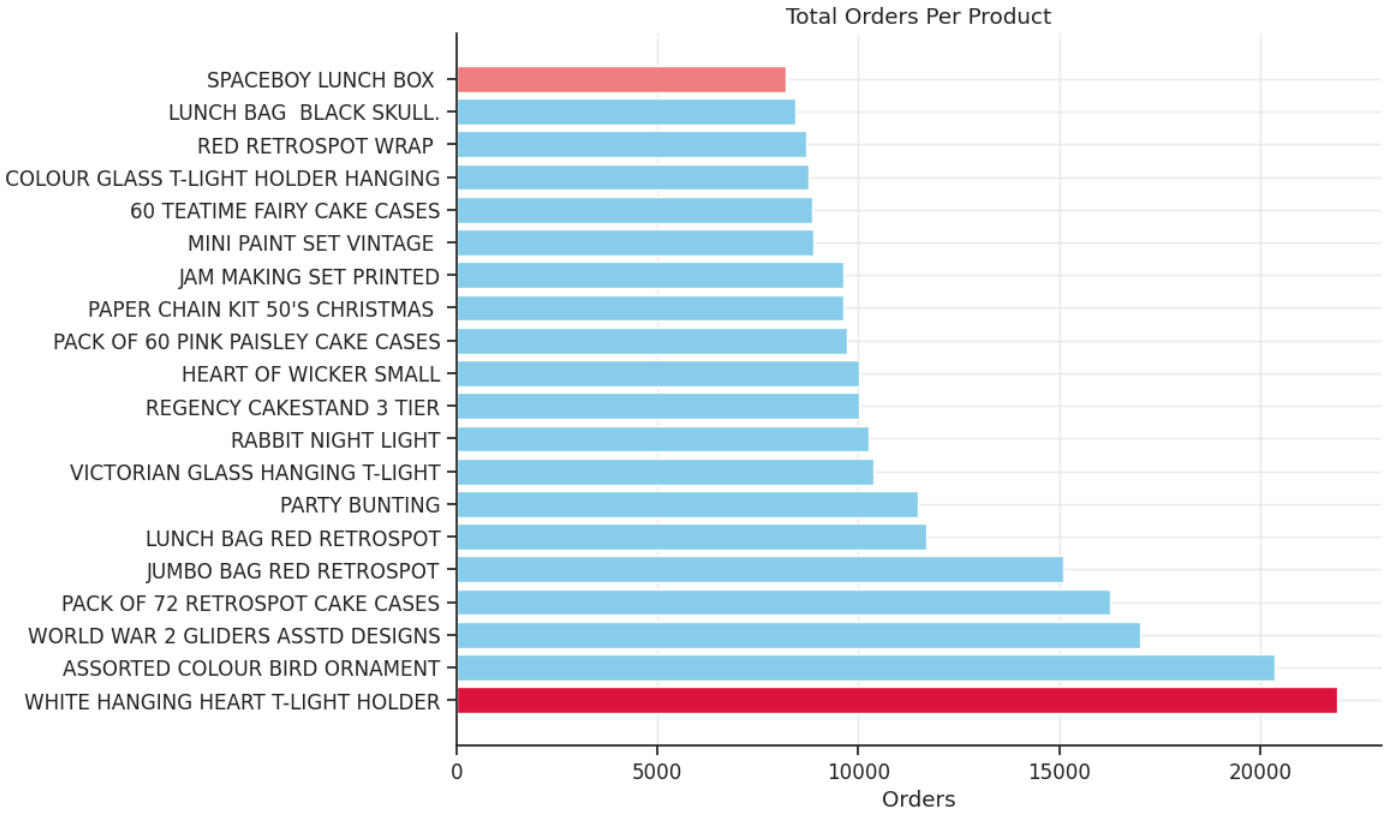
Out[52]:

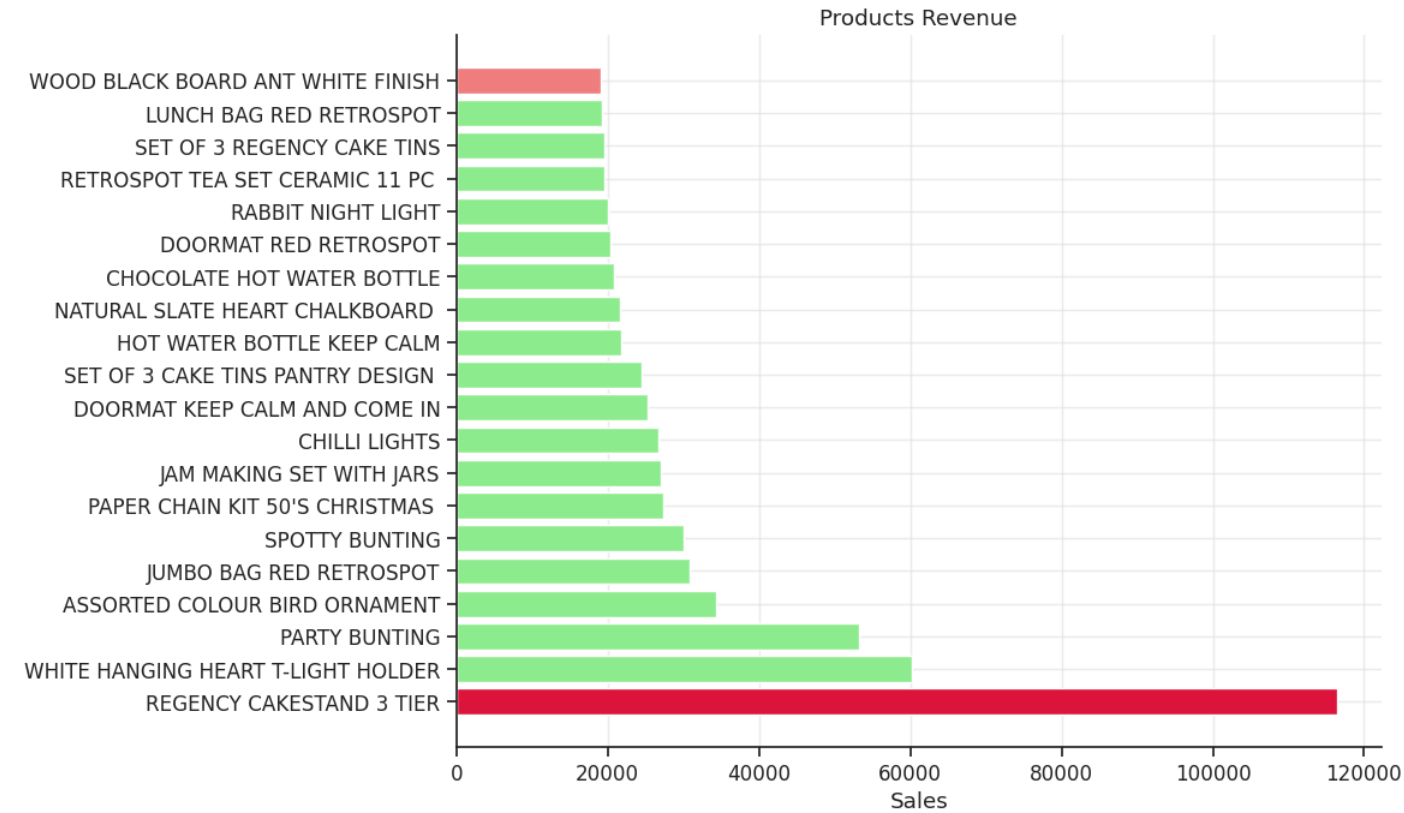
	Hour	total_orders	revenue	orders_pct	revenue_pct
0	6	1	4.25	0.0001	0.0000
14	20	18	5473.98	0.0010	0.0009
1	7	26	14015.64	0.0015	0.0023
13	19	141	35808.94	0.0080	0.0059
12	18	157	45444.93	0.0089	0.0075

In [53]:
```
orders_sorted = products.sort_values('orders', ascending=False).head(20)
revenue_sorted = products.sort_values('sales', ascending=False).head(20)
```

In [54]:

```
orders_colors = ['crimson' if x == orders_sorted['orders'].max() else 'lightcoral' if x == orders_sorted['orders'].min() else 'skyblue' for x in orders_sorted['orders']]
revenue_colors = ['crimson' if x == revenue_sorted['sales'].max() else 'lightcoral' if x == revenue_sorted['sales'].min() else 'lightgreen' for x in revenue_sorted['sales']]

fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 14))

# Plot 1: Total Orders
ax1.barh(orders_sorted['Description'], orders_sorted['orders'], color=orders_colors)
ax1.set_title('Total Orders Per Product')
ax1.set_xlabel('Orders')

# Plot 2: Revenue
ax2.barh(revenue_sorted['Description'], revenue_sorted['sales'], color=revenue_colors)
ax2.set_title('Products Revenue')
ax2.set_xlabel('Sales')

plt.tight_layout()
plt.savefig('Products_Bar.png')
plt.show()
```


Total Orders Per Product
SPACEBOY LUNCH BOX
LUNCH BAG BLACK SKULL.
RED RETROSPOT WRAP
COLOUR GLASS T-LIGHT HOLDER HANGING
60 TEATIME FAIRY CAKE CASES
MINI PAINT SET VINTAGE
JAM MAKING SET PRINTED
PAPER CHAIN KIT 50'S CHRISTMAS
PACK OF 60 PINK PAISLEY CAKE CASES
HEART OF WICKER SMALL
REGENCY CAKESTAND 3 TIER
RABBIT NIGHT LIGHT
VICTORIAN GLASS HANGING T-LIGHT
PARTY BUNTING
LUNCH BAG RED RETROSPOT
JUMBO BAG RED RETROSPOT
PACK OF 72 RETROSPOT CAKE CASES
WORLD WAR 2 GLIDERS ASSTD DESIGNS
ASSORTED COLOUR BIRD ORNAMENT
WHITE HANGING HEART T-LIGHT HOLDER
0
5000
10000
15000
20000
Orders


Products Revenue
WOOD BLACK BOARD ANT WHITE FINISH
LUNCH BAG RED RETROSPOT
SET OF 3 REGENCY CAKE TINS
RETROSPOT TEA SET CERAMIC 11 PC
RABBIT NIGHT LIGHT
DOORMAT RED RETROSPOT
CHOCOLATE HOT WATER BOTTLE
NATURAL SLATE HEART CHALKBOARD
HOT WATER BOTTLE KEEP CALM
SET OF 3 CAKE TINS PANTRY DESIGN
DOORMAT KEEP CALM AND COME IN
CHILLI LIGHTS
JAM MAKING SET WITH JARS
PAPER CHAIN KIT 50'S CHRISTMAS
SPOTTY BUNTING
JUMBO BAG RED RETROSPOT
ASSORTED COLOUR BIRD ORNAMENT
PARTY BUNTING
WHITE HANGING HEART T-LIGHT HOLDER
REGENCY CAKESTAND 3 TIER
0
20000
40000
60000
80000
100000
120000
Sales

In [55]:
```
# mop = most_ordered_product
mop_series = orders_sorted.iloc[0]

# tsp = top_selling_product
tsp_series = revenue_sorted.iloc[0]

print(f'Most Ordered Product: {mop_series.Description}')
print(f'  Total Orders: {mop_series["orders"]}')
print(f'  Total Sales: ${mop_series["sales"]:,.2f}')
print(f'  Average Unit Price: ${mop_series["avg_unit_price"]:,.2f}')
print()
print(f'Top Selling Product: {tsp_series.Description}')
print(f'  Total Orders: {tsp_series["orders"]}')
print(f'  Total Sales: ${tsp_series["sales"]:,.2f}')
print(f'  Average Unit Price: ${tsp_series["avg_unit_price"]:,.2f}')
```

```
Most Ordered Product: WHITE HANGING HEART T-LIGHT HOLDER
  Total Orders: 21921
  Total Sales: $60,187.91
  Average Unit Price: $2.90

Top Selling Product: REGENCY CAKESTAND 3 TIER
  Total Orders: 10035
  Total Sales: $116,442.55
  Average Unit Price: $12.43
```

In [56]:
```
# lop = least_ordered_product
lop_series = orders_sorted.iloc[-1]

# lsp = lowest_selling_product
lsp_series = revenue_sorted.iloc[-1]

print(f'Least Ordered Product: {lop_series.Description}')
print(f'  Total Orders: {lop_series["orders"]}')
print(f'  Total Sales: ${lop_series["sales"]:,.2f}')
print(f'  Average Unit Price: ${lop_series["avg_unit_price"]:,.2f}')
print()
print(f'Lowest Selling Product: {lsp_series.Description}')
print(f'  Total Orders: {lsp_series["orders"]}')
print(f'  Total Sales: ${lsp_series["sales"]:,.2f}')
print(f'  Average Unit Price: ${lsp_series["avg_unit_price"]:,.2f}')
```

```
Least Ordered Product: SPACEBOY LUNCH BOX
  Total Orders: 8212
  Total Sales: $15,274.74
  Average Unit Price: $1.94

Lowest Selling Product: WOOD BLACK BOARD ANT WHITE FINISH
  Total Orders: 2746
  Total Sales: $19,173.15
  Average Unit Price: $7.53
```

products frequently bought together

In [57]:
```
# Remove leading/trailing whitespace from Description
customer_df['Description'] = customer_df['Description'].str.strip()
```

In [58]:
```
# Group by InvoiceNo and create a list of products for each invoice
basket = customer_df.groupby('InvoiceNo')['Description'].apply(list).reset_index()
basket
```

Out[58]:

	InvoiceNo	Description
0	536365	[WHITE HANGING HEART T-LIGHT HOLDER, WHITE MET...
1	536366	[HAND WARMER UNION JACK, HAND WARMER RED POLKA...
2	536367	[ASSORTED COLOUR BIRD ORNAMENT, POPPY'S PLAYHO...
3	536368	[JAM MAKING SET WITH JARS, RED COAT RACK PARIS...
4	536369	[BATH BUILDING BLOCK WORD]
...	...	...
17626	581583	[LUNCH BAG RED RETROSPOT, 6 CHOCOLATE LOVE HEA...
17627	581584	[6 CHOCOLATE LOVE HEART T-LIGHTS]
17628	581585	[BLACK TEATOWEL CLASSIC DESIGN, ASSORTED BOTT...
17629	581586	[LARGE CAKE STAND HANGING STRAWBERY, SET OF 3...
17630	581587	[CIRCUS PARADE LUNCH BOX, PLASTERS IN TIN CIRC...

17631 rows × 2 columns

In [59]:
```
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules

# One-hot encode the data
te = TransactionEncoder()
te_ary = te.fit(basket['Description']).transform(basket['Description'])
df_encoded = pd.DataFrame(te_ary, columns=te.columns_)

# Find frequent itemsets using apriori
frequent_itemsets = apriori(df_encoded, min_support=0.01, use_colnames=True)
```

In [60]:
```
frequent_itemsets
```

Out[60]:

	support	itemsets
0	0.013102	(10 COLOUR SPACEBOY PEN)
1	0.010606	(12 MESSAGE CARDS WITH ENVELOPES)
2	0.015484	(12 PENCIL SMALL TUBE WOODLAND)
3	0.016959	(12 PENCILS SMALL TUBE RED RETROSPOT)
4	0.015824	(12 PENCILS SMALL TUBE SKULL)
...	...	...
995	0.010550	(POPPY'S PLAYHOUSE LIVINGROOM, POPPY'S PLAYHOU...
996	0.010266	(REGENCY TEAPLATE GREEN, REGENCY TEAPLATE PI...
997	0.010153	(WOODEN STAR CHRISTMAS SCANDINAVIAN, WOODEN TR...
998	0.012932	(PINK REGENCY TEACUP AND SAUCER, ROSES REGENCY...
999	0.010663	(LUNCH BAG BLACK SKULL., LUNCH BAG CARS BLUE,...

1000 rows × 2 columns

In [61]:

```
# Generate the association rules
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)

# Sort the rules by confidence and lift for the best recommendations
rules = rules.sort_values(['confidence', 'lift'], ascending=[False, False])

# Display the top rules
print(rules.head())
```

```
                                    antecedents  \
950  (REGENCY TEA PLATE PINK, REGENCY TEA PLATE ROSES)
948  (REGENCY TEA PLATE GREEN, REGENCY TEA PLATE PINK)
956  (WOODEN HEART CHRISTMAS SCANDINAVIAN, WOODEN T...
942  (POPPY'S PLAYHOUSE LIVINGROOM, POPPY'S PLAYHOU...
549                        (REGENCY TEA PLATE PINK)

                         consequents  antecedent support  \
950            (REGENCY TEA PLATE GREEN)            0.010947
948            (REGENCY TEA PLATE ROSES)            0.011230
956  (WOODEN STAR CHRISTMAS SCANDINAVIAN)            0.011117
942          (POPPY'S PLAYHOUSE KITCHEN)            0.011627
549            (REGENCY TEA PLATE GREEN)            0.012478

     consequent support   support  confidence       lift  representativity  \
950            0.014974  0.010266    0.937824  62.631712               1.0
948            0.018150  0.010266    0.914141  50.366335               1.0
956            0.023935  0.010153    0.913265  38.155878               1.0
942            0.019625  0.010550    0.907317  46.233836               1.0
549            0.014974  0.011230    0.900000  60.105682               1.0

     leverage  conviction  zhangs_metric   jaccard  certainty  kulczynski
950  0.010102   15.842508       0.994925  0.655797   0.936879    0.811715
948  0.010062   11.435666       0.991278  0.537092   0.912554    0.739883
956  0.009886   11.253454       0.984739  0.407745   0.911138    0.668718
942  0.010321   10.577735       0.989880  0.509589   0.905462    0.722445
549  0.011043    9.850264       0.995788  0.692308   0.898480    0.825000
```

In [62]:

```
rules
```

Out[62]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulczynski
950	(REGENCY TEA PLATE PINK, REGENCY TEA PLATE ROSES)	(REGENCY TEA PLATE GREEN)	0.010947	0.014974	0.010266	0.937824	62.631712	1.0	0.010102	15.842508	0.994925	0.655797	0.936879	0.811715
948	(REGENCY TEA PLATE GREEN, REGENCY TEA PLATE PINK)	(REGENCY TEA PLATE ROSES)	0.011230	0.018150	0.010266	0.914141	50.366335	1.0	0.010062	11.435666	0.991278	0.537092	0.912554	0.739883
956	(WOODEN HEART CHRISTMAS SCANDINAVIAN, WOODEN T...	(WOODEN STAR CHRISTMAS SCANDINAVIAN)	0.011117	0.023935	0.010153	0.913265	38.155878	1.0	0.009886	11.253454	0.984739	0.407745	0.911138	0.668718
942	(POPPY'S PLAYHOUSE LIVINGROOM, POPPY'S PLAYHOU...	(POPPY'S PLAYHOUSE KITCHEN)	0.011627	0.019625	0.010550	0.907317	46.233836	1.0	0.010321	10.577735	0.989880	0.509589	0.905462	0.722445
549	(REGENCY TEA PLATE PINK)	(REGENCY TEA PLATE GREEN)	0.012478	0.014974	0.011230	0.900000	60.105682	1.0	0.011043	9.850264	0.995788	0.692308	0.898480	0.825000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
456	(WHITE HANGING HEART T-LIGHT HOLDER)	(LUNCH BAG SPACEBOY DESIGN)	0.108786	0.054903	0.010550	0.096976	1.766306	1.0	0.004577	1.046591	0.486804	0.068889	0.044517	0.144562
406	(WHITE HANGING HEART T-LIGHT HOLDER)	(LUNCH BAG CARS BLUE)	0.108786	0.053315	0.010436	0.095933	1.799361	1.0	0.004636	1.047140	0.498474	0.068811	0.045018	0.145839
590	(WHITE HANGING HEART T-LIGHT HOLDER)	(SET/5 RED RETROSPOT LID GLASS BOWLS)	0.108786	0.042992	0.010096	0.092805	2.158635	1.0	0.005419	1.054908	0.602262	0.071257	0.052050	0.163817
465	(WHITE HANGING HEART T-LIGHT HOLDER)	(LUNCH BAG SUKI DESIGN)	0.108786	0.049799	0.010039	0.092284	1.853135	1.0	0.004622	1.046804	0.516569	0.067583	0.044712	0.146939
355	(WHITE HANGING HEART T-LIGHT HOLDER)	(LUNCH BAG BLACK SKULL.)	0.108786	0.058136	0.010039	0.092284	1.587368	1.0	0.003715	1.037619	0.415194	0.063991	0.036255	0.132483

988 rows × 14 columns

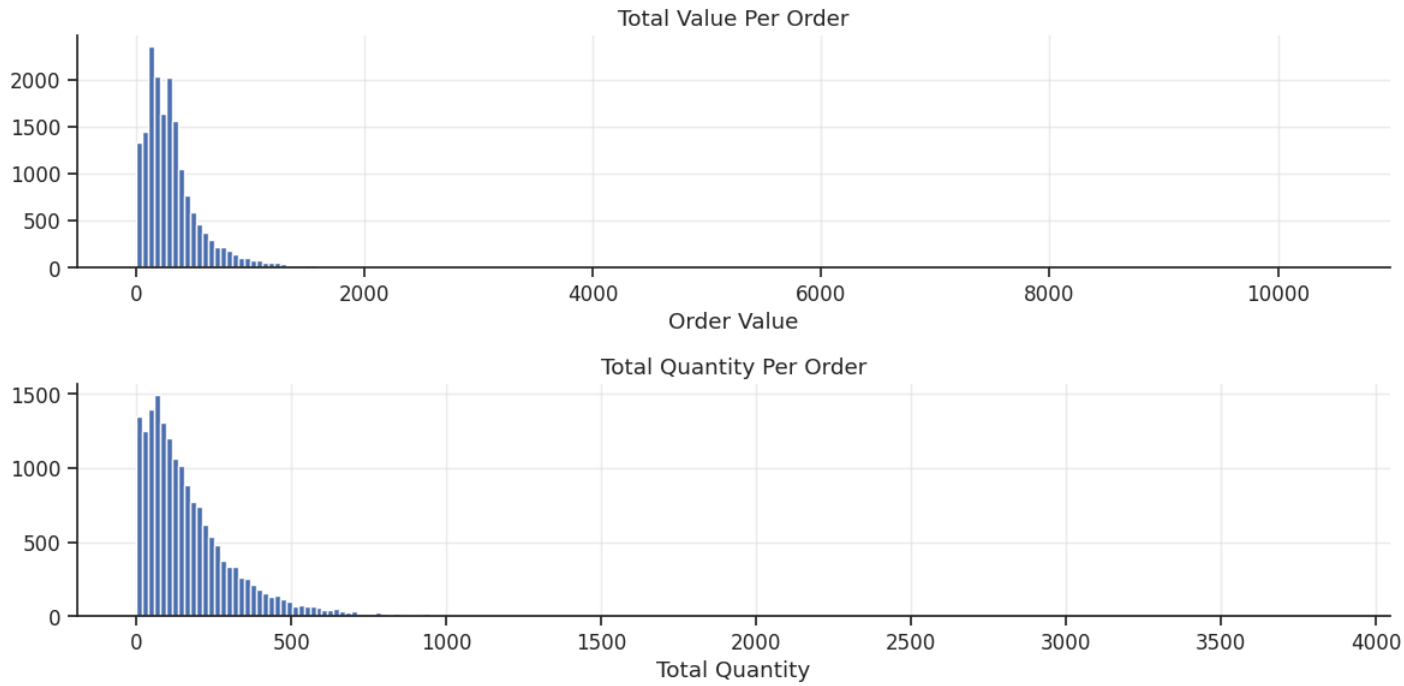
distribution of order values

In [63]:
```
order_values = customer_df.groupby('InvoiceNo').agg(
    value=('TotalPrice','sum'),
    quantity=('Quantity','sum')
).reset_index().sort_values(by='value',ascending=False)
order_values.head()
```

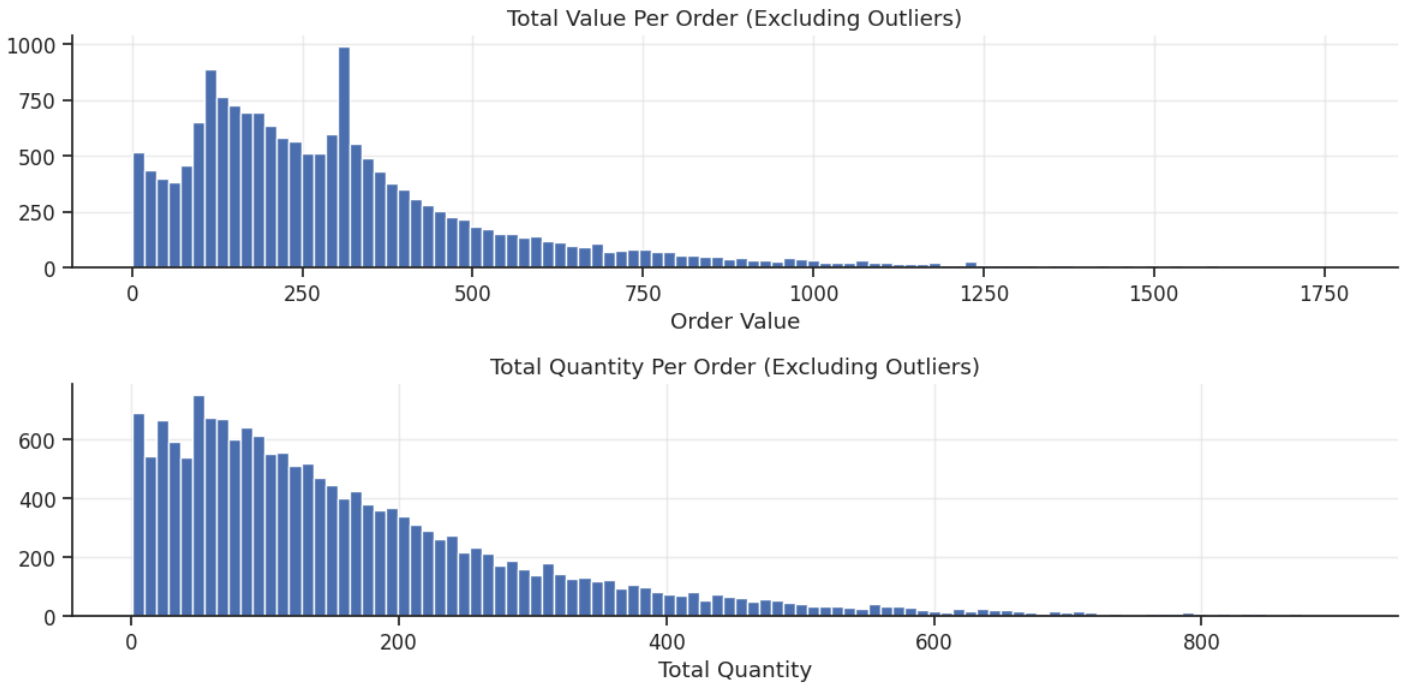
Out[63]:

	InvoiceNo	value	quantity
16309	578305	10462.47	2103
9114	560580	8506.31	2437
13381	571281	7975.46	1609
1917	541789	6958.14	1837
15429	576339	6878.64	2171

In [64]:
```
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 6))

ax1.hist(order_values['value'],bins=200)
ax1.set_title('Total Value Per Order')
ax1.set_xlabel('Order Value')

ax2.hist(order_values['quantity'],bins=200)
ax2.set_title('Total Quantity Per Order')
ax2.set_xlabel('Total Quantity')

plt.tight_layout()
plt.savefig('quantity_order_value.png')
plt.show()
```



In [65]:
```
# --- Corrected Code ---
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 6))

# Calculate the 99th percentile to identify outliers
value_cutoff = order_values['value'].quantile(0.99)
quantity_cutoff = order_values['quantity'].quantile(0.99)

# Filter the data to exclude the top 1%
filtered_values = order_values[order_values['value'] < value_cutoff]
filtered_quantity = order_values[order_values['quantity'] < quantity_cutoff]

# Plot 1: Total Value (filtered)
ax1.hist(filtered_values['value'], bins=100)
ax1.set_title('Total Value Per Order (Excluding Outliers)')
ax1.set_xlabel('Order Value')

# Plot 2: Total Quantity (filtered)
ax2.hist(filtered_quantity['quantity'], bins=100)
ax2.set_title('Total Quantity Per Order (Excluding Outliers)')
ax2.set_xlabel('Total Quantity')

plt.tight_layout()
plt.savefig('quantity_order_value_filterd.png')

plt.show()
```



In [66]:
```
(order_values[(order_values['value']< 700) & (order_values['value']>= 1)].shape[0] / order_values.shape[0])*100
```

Out[66]:
```
90.85134138732913
```

In [67]:
```
(order_values[(order_values['quantity']< 400) & (order_values['quantity']>= 1)].shape[0] / order_values.shape[0])*100
```

Out[67]:
```
90.85134138732913
```

90% of orders quantity ranges between 1 and 400, while 90% of order value ranges from 1 to 700$

Conclusion & Strategic Recommendations

This data-driven analysis reveals a clear picture of the company's performance, customer base, and significant opportunities for growth and optimization. The key to future success lies in moving from a broad strategy to a targeted one.

1. Dominant Market with Concentrated Value: The business is overwhelmingly reliant on the UK market and a small group of high-value **"Champion"** customers. While this provides a stable revenue base, it also represents a risk. The immediate strategy must be to **protect and nurture this core segment** through loyalty programs and exclusive offers, while also developing targeted strategies for secondary markets like the Netherlands, which show higher revenue potential per order.

2. Critical Customer Retention Challenge: The analysis uncovers a pressing issue: **customer retention is declining.** While we successfully acquire new customers, we are failing to bring them back. The large segment of **"Potential Loyalists"** and the high-value **"At-Risk"** customers represent the greatest immediate opportunity. Launching win-back campaigns and post-purchase nurturing sequences is not just beneficial—it is urgent to secure long-term profitability.

3. Clear Operational Levers to Pull: The business is not operating at a consistent capacity throughout the week. The data provides a clear blueprint for optimization:

- **Focus marketing efforts** (email campaigns, ad spend) during the high-activity **mid-week period (Mon-Thu)**, especially around **noon**.
- **Align staffing and resource allocation** to this schedule to maximize efficiency and customer service during peak demand.

4. Product and Pricing Strategy Insights: The divergence between most-ordered and top-revenue generating products highlights a successful premium product strategy. The focus should be on **promoting high-margin items** like the "REGENCY CAKESTAND" to increase average order value, particularly among the loyal customer base.

In summary, the path forward is clear: **Shift from mass marketing to personalized customer lifecycle management.** By protecting high-value clients, re-engaging at-risk segments, and optimizing operations around clear data-driven patterns, this business can unlock significant growth and build a more resilient, loyal customer base.

Author

Ahmed A.Elatwy