E-commerce User Behavior Analysis

This project explores user interaction data from a multi-category e-commerce store to understand browsing, carting, and purchasing behavior.

Objectives

- Analyze customer flow: view → cart → purchase
- Identify popular categories and peak activity times
- Clean and structure data for reliable insights
- Visualize user behavior with meaningful charts

Dataset

- *Source:* Kaggle (9.1 GB, sample of 5_000_000 rows used)
- *Key Columns:* event_time, event_type, category_code, brand, price

Tools

- pandas, seaborn, matplotlib
- Jupyter Notebook for analysis

In [1]:
```
#importing necessary libraries and loading the dataset


import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import os

# Read only the required columns and limit rows to avoid MemoryError
df = pd.read_csv('2019-Nov.csv', nrows=5_000_000)
# Downcast int64 columns to int8 and float64 columns to float32
for col in df.select_dtypes(include=['int64']).columns:
    df[col] = pd.to_numeric(df[col], downcast='integer')
for col in df.select_dtypes(include=['float64']).columns:
    df[col] = pd.to_numeric(df[col], downcast='float')
df.to_parquet('2019-Nov.parquet')
```

In [2]:
```
# I am using the parquet file for further analysis to save memory and speed up p

df = pd.read_parquet('2019-Nov.parquet')
```

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

Out[3]:

	event_time	event_type	product_id	category_id	category_code
0	2019-11-01 00:00:00 UTC	view	1003461	2053013555631882655	electronics.smartphone
1	2019-11-01 00:00:00 UTC	view	5000088	2053013566100866035	appliances.sewing_machine
2	2019-11-01 00:00:01 UTC	view	17302664	2053013553853497655	None
3	2019-11-01 00:00:01 UTC	view	3601530	2053013563810775923	appliances.kitchen.washer
4	2019-11-01 00:00:01 UTC	view	1004775	2053013555631882655	electronics.smartphone

In [4]:

```
# Display the shape of the DataFrame to confirm successful loading
df.shape
```

Out[4]:

```
(5000000, 9)
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000000 entries, 0 to 4999999
Data columns (total 9 columns):
 #   Column         Dtype  
---  ------         -----  
 0   event_time     object 
 1   event_type     object 
 2   product_id     int32  
 3   category_id    int64  
 4   category_code  object 
 5   brand          object 
 6   price          float32
 7   user_id        int32  
 8   user_session   object 
dtypes: float32(1), int32(2), int64(1), object(5)
memory usage: 286.1+ MB
```

Cleaning the data

In [6]:

```
# Checking for missing values in the dataset
df.isnull().sum()
```

Out[6]:
```
event_time              0
event_type              0
product_id              0
category_id             0
category_code     1602394
brand              727867
price                   0
user_id                 0
user_session            0
dtype: int64
```

In [7]:
```
# Calculating the percentage of missing values in the 'category_code'and 'brand'
df['category_code'].isnull().mean()*100
```

Out[7]:
```
np.float64(32.04788)
```

In [8]:
```
# Calculating the percentage of missing values in the 'brand' column
df['brand'].isnull().mean() * 100
```

Out[8]:
```
np.float64(14.55734)
```

In [9]:
```
for col in ['category_code', 'brand']:
    null_ratio = df[col].isna().mean() * 100
    if null_ratio < 10:
        df[col] = df[col].fillna("unknown")
    else:
        df.dropna(subset=[col], inplace=True)
```

In [10]:
```
df
```

Out[10]:

	event_time	event_type	product_id	category_id	categ
0	2019-11-01 00:00:00 UTC	view	1003461	2053013555631882655	electronics.sn
1	2019-11-01 00:00:00 UTC	view	5000088	2053013566100866035	appliances.sewing
3	2019-11-01 00:00:01 UTC	view	3601530	2053013563810775923	appliances.kitch
4	2019-11-01 00:00:01 UTC	view	1004775	2053013555631882655	electronics.sn
5	2019-11-01 00:00:01 UTC	view	1306894	2053013558920217191	computers
...	...	...	...	...	
4999993	2019-11-04 07:09:03 UTC	view	1005115	2053013555631882655	electronics.sn
4999994	2019-11-04 07:09:03 UTC	view	1801739	2053013554415534427	electroni
4999995	2019-11-04 07:09:03 UTC	view	2701880	2053013563911439225	appliances.kitchen.re
4999997	2019-11-04 07:09:03 UTC	view	3601290	2053013563810775923	appliances.kitch
4999998	2019-11-04 07:09:03 UTC	view	5000691	2053013566100866035	appliances.sewing

3397606 rows × 9 columns

In [11]:

```
# Checking the number of missing values in the 'brand' and 'category_code' colum
df["brand"].isnull().sum()
```

Out[11]:
```
np.int64(0)
```

In [12]:
```
df["category_code"].isnull().sum()
```

Out[12]:
```
np.int64(0)
```

In [13]:
```
df.isnull().sum()
```

Out[13]:
```
event_time       0
event_type       0
product_id       0
category_id      0
category_code    0
brand            0
price            0
user_id          0
user_session     0
dtype: int64
```

In [14]:
```
df.shape
```

Out[14]:
```
(3397606, 9)
```

Converting the event_time to Datetime data

In [15]:
```
df["event_time"]=pd.to_datetime(df["event_time"], format="%Y-%m-%d %H:%M:%S UTC"
```

In [16]:
```
# Extracting hour from the 'event_time' column(0-23)
df['hour'] = df['event_time'].dt.hour
# Extracting day from the 'event_time' column(1-31)
df['day'] = df['event_time'].dt.day
# Extracting day of week from the 'event_time' column(Monday-Sunday)
df['day_of_week'] = df['event_time'].dt.day_name()

def times_of_day(hour):
    if 5<=hour <=12:
        return 'morning'
    elif 12<= hour <=16:
        return 'afternoon'
    elif 16<= hour <=19:
        return 'evening'
    else:
        return 'night'
# Applying the function to create a new column 'time_of_day'
df['time_of_day'] = df['hour'].apply(times_of_day)
```

In [17]:
```
# Displaying the first few rows of the DataFrame to verify the new columns
df.head()
```

Out[17]:

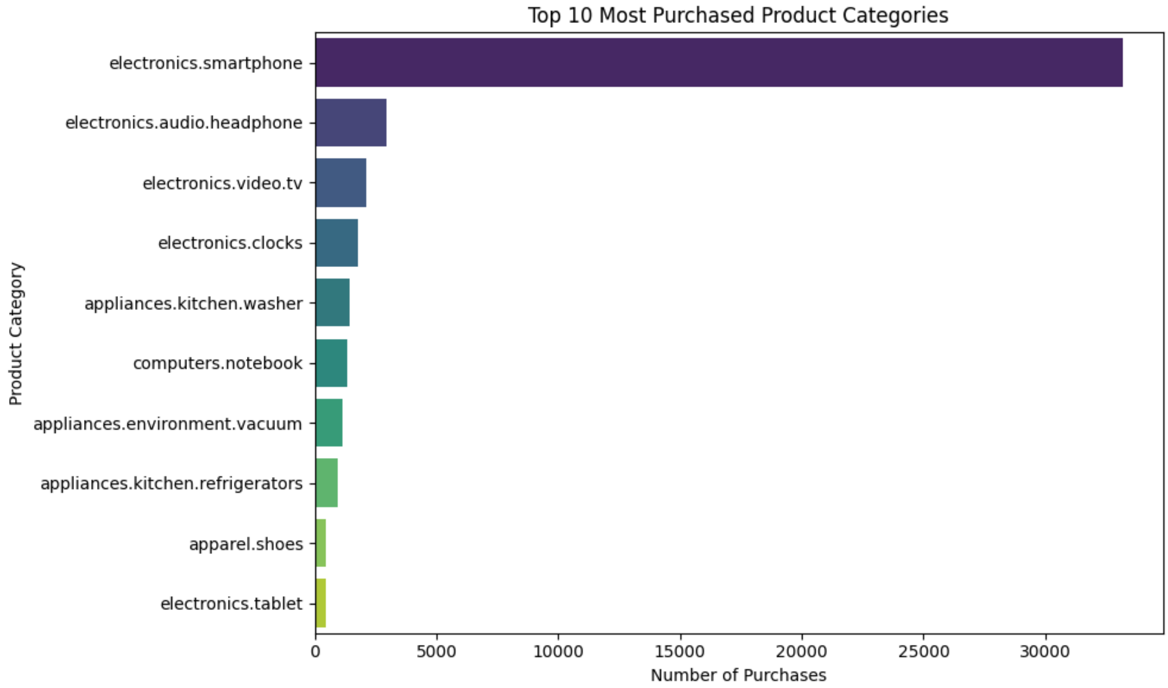
	event_time	event_type	product_id	category_id	category_code
0	2019-11-01 00:00:00	view	1003461	2053013555631882655	electronics.smartphone
1	2019-11-01 00:00:00	view	5000088	2053013566100866035	appliances.sewing_machine
3	2019-11-01 00:00:01	view	3601530	2053013563810775923	appliances.kitchen.washer
4	2019-11-01 00:00:01	view	1004775	2053013555631882655	electronics.smartphone
5	2019-11-01 00:00:01	view	1306894	2053013558920217191	computers.notebook

Top product category

In [18]:

```
# Filter for purchase events and count occurrences by category_code
purchase_counts = df[df['event_type'] == 'purchase']['category_code'].value_coun

# Plot the top purchased product categories
plt.figure(figsize=(10,6))
sns.barplot(x=purchase_counts.values, y=purchase_counts.index, palette='viridis'
plt.xlabel('Number of Purchases')
plt.ylabel('Product Category')
plt.title('Top 10 Most Purchased Product Categories')
plt.tight_layout()
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_9320\3826131209.py:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.barplot(x=purchase_counts.values, y=purchase_counts.index, palette='viridi
s')
```

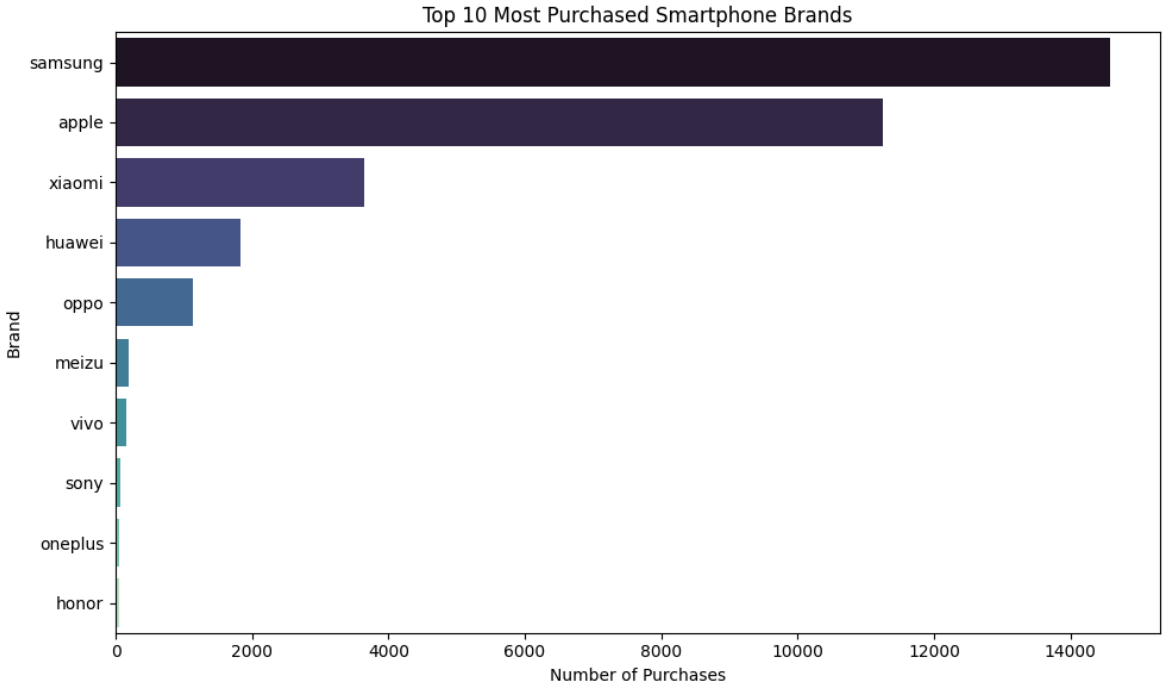


Lets see which brand has the most selling smartphone

In [19]:

```
# Filter for purchases in the 'electronics.smartphone' category
smartphone_purchases = df[(df['event_type'] == 'purchase') & (df['category_code'

# Count purchases by brand
brand_counts = smartphone_purchases['brand'].value_counts().head(10)

# Plot the top purchased smartphone brands
plt.figure(figsize=(10,6))
sns.barplot(x=brand_counts.values, y=brand_counts.index, palette='mako')
plt.xlabel('Number of Purchases')
plt.ylabel('Brand')
plt.title('Top 10 Most Purchased Smartphone Brands')
plt.tight_layout()
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_9320\4004140150.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.barplot(x=brand_counts.values, y=brand_counts.index, palette='mako')
```

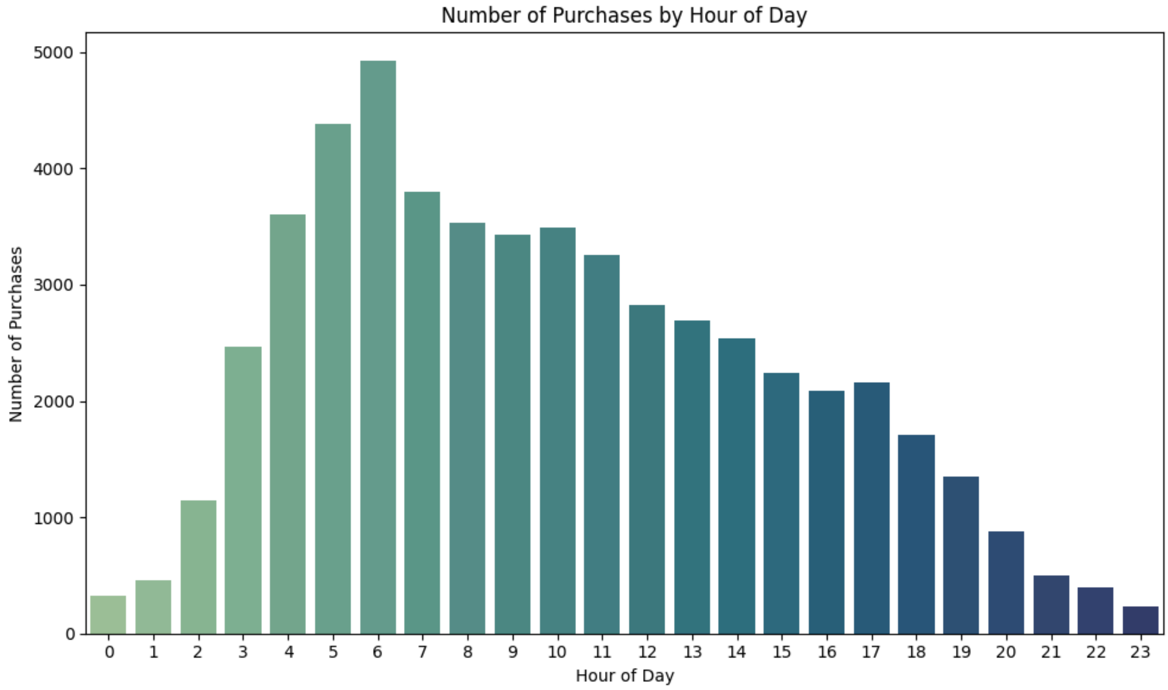


Lets see at which time customers buys most product

In [20]:

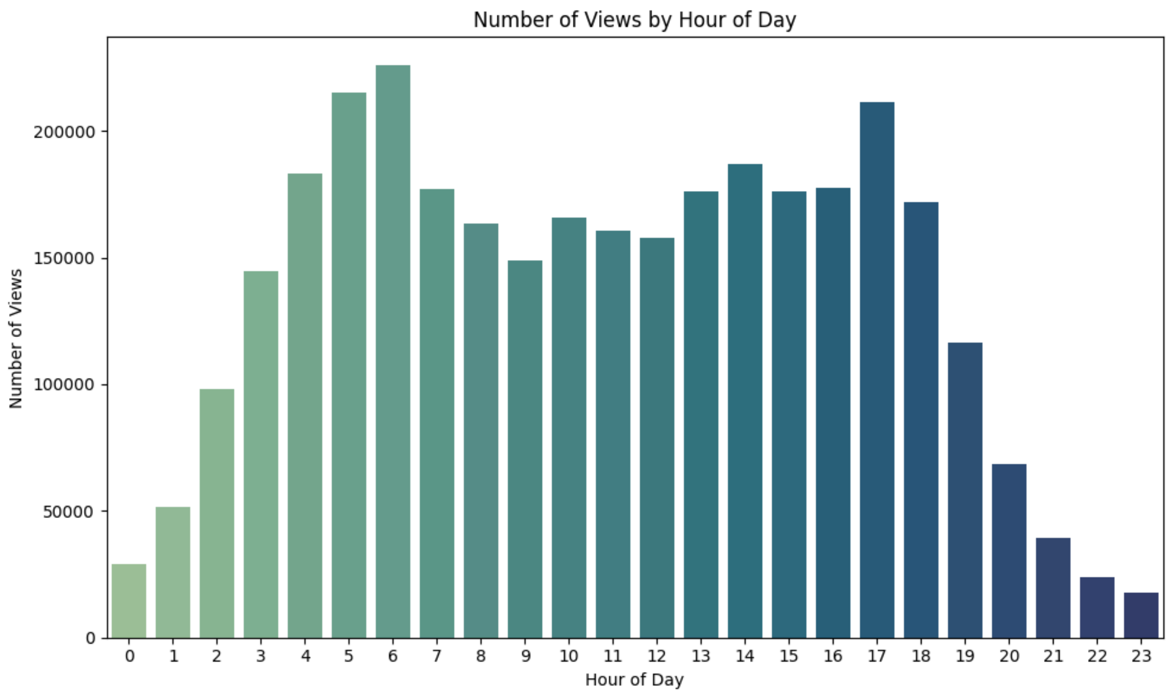
```
# Group by 'hour' and count the number of purchase events
hourly_sales = df[df['event_type'] == 'purchase']['hour'].value_counts().sort_in

# Plot sales by hour
plt.figure(figsize=(10,6))
sns.barplot(x=hourly_sales.index, y=hourly_sales.values, palette='crest')
plt.xlabel('Hour of Day')
plt.ylabel('Number of Purchases')
plt.title('Number of Purchases by Hour of Day')
plt.tight_layout()
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_9320\250231619.py:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.barplot(x=hourly_sales.index, y=hourly_sales.values, palette='crest')
```



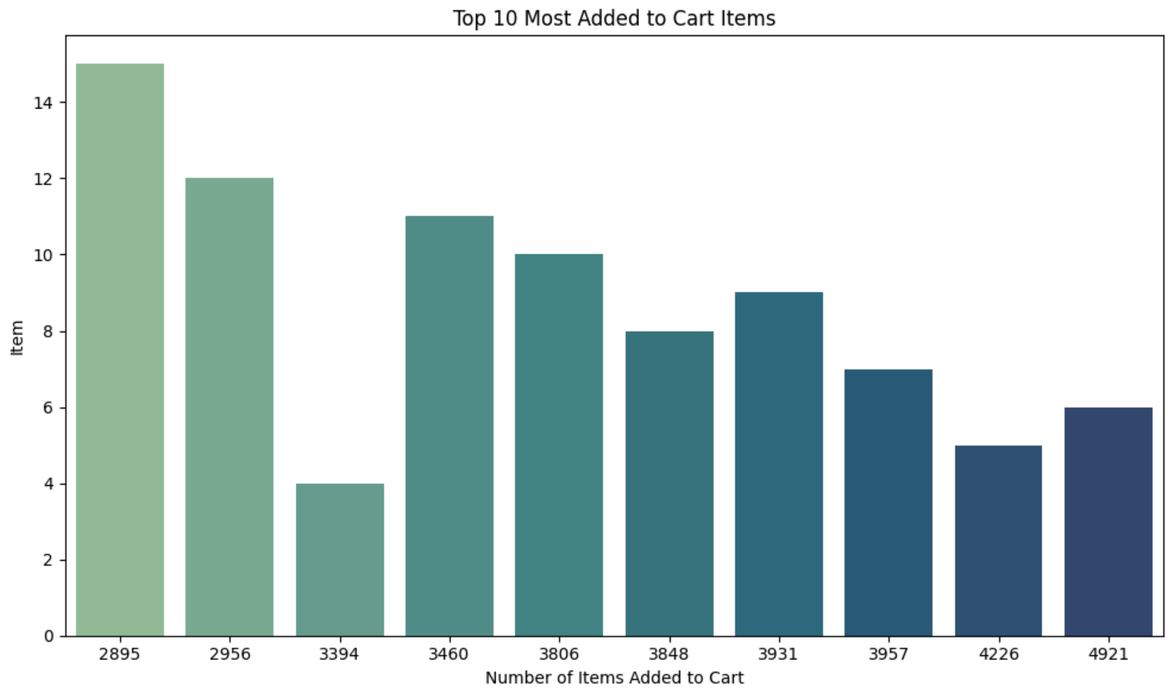
In [21]:
```
hourly_view= df[df['event_type'] == 'view']['hour'].value_counts().sort_index()
# Plot views by hour
plt.figure(figsize=(10,6))
sns.barplot(x=hourly_view.index, y=hourly_view.values, palette='crest')
plt.xlabel('Hour of Day')
plt.ylabel('Number of Views')
plt.title('Number of Views by Hour of Day')
plt.tight_layout()
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_9320\287847805.py:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.barplot(x=hourly_view.index, y=hourly_view.values, palette='crest')
```



In [22]:
```
item_added_cart=df[df['event_type'] == 'cart']['hour'].value_counts().head(10)
plt.figure(figsize=(10,6))
sns.barplot(x=item_added_cart.values, y=item_added_cart.index, palette='crest')
plt.xlabel('Number of Items Added to Cart')
plt.ylabel('Item')
plt.title('Top 10 Most Added to Cart Items')
plt.tight_layout()
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_9320\3395226965.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.barplot(x=item_added_cart.values, y=item_added_cart.index, palette='crest')
```



Finding out each customer RFM values

In [23]:
```
df.tail()
```

Out[23]:

	event_time	event_type	product_id	category_id	categ
4999993	2019-11-04 07:09:03	view	1005115	2053013555631882655	electronics.sn
4999994	2019-11-04 07:09:03	view	1801739	2053013554415534427	electroni
4999995	2019-11-04 07:09:03	view	2701880	2053013563911439225	appliances.kitchen.re
4999997	2019-11-04 07:09:03	view	3601290	2053013563810775923	appliances.kitch
4999998	2019-11-04 07:09:03	view	5000691	2053013566100866035	appliances.sewing

In [24]:

```
#lets calculate the recency
# Recency: days since last purchase for each user
latest_date = df['event_time'].max()
recency = df[df['event_type'] == 'purchase'].groupby('user_id')['event_time'].ma
recency = (latest_date - recency).dt.days
recency.head()
```

Out[24]:

```
user_id
356520186    3
428293417    1
447698613    1
460752410    0
467047496    0
Name: event_time, dtype: int64
```

In [29]:

```
#Now lets calculate the frequency
# Frequency: number of purchases in the last 30 days for each user
frequency = df.drop_duplicates(subset=['user_id', 'event_time']).groupby('user_i
frequency = frequency[frequency.index.isin(recency.index)]  # Ensure frequency m
frequency.head()
```

Out[29]:

```
user_id
356520186    10
428293417     5
447698613     3
460752410     6
467047496     5
dtype: int64
```

In [30]:

```
#monetary value: total amount spent by each user in the last 30 days
monetary = df[df['event_type'] == 'purchase'].groupby('user_id')['price'].sum()
```

```
monetary = monetary[monetary.index.isin(recency.index)]  # Ensure monetary match
monetary.head()
```

Out[30]:
```
user_id
356520186      33.450001
428293417    1575.500000
447698613     282.859985
460752410     921.979980
467047496     396.149994
Name: price, dtype: float32
```

In [31]:
```
# Createing a medal system based on monetary value

rfm = pd.DataFrame({'monetary': monetary})

def assign_medal(amount):
    if amount > 5000:
        return 'gold'
    elif amount > 1000:
        return 'silver'
    elif amount > 500:
        return 'bronze'
    else:
        return 'no medal'

rfm['medal'] = rfm['monetary'].apply(assign_medal)
rfm.head()
```

Out[31]:

user_id	monetary	medal
356520186	33.450001	no medal
428293417	1575.500000	silver
447698613	282.859985	no medal
460752410	921.979980	bronze
467047496	396.149994	no medal

Conclusion

This analysis of 5 million rows of e-commerce data provided valuable insights into customer behavior. Here's what we learned:

- **Smartphones and electronics** are among the most purchased items.
- **Purchases peak during the evening and late afternoon**, indicating high engagement post-work hours.
- **Cart additions** are most frequent around mid-day, hinting at lunchtime browsing behavior.
- **RFM analysis** allowed segmentation of users by value, revealing that only a few high-value users qualify for a 'gold' or 'silver' tier.