Ecommerce Consumer Behavior Insights (ECBI)

July 13, 2025

[73]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[74]:
```python
df = pd.read_csv(r'../data/Ecommerce_Consumer_Behavior_Analysis_Data.csv')

print(df.head())
print(df.info())
```

```
   Customer_ID  Age  Gender Income_Level Marital_Status Education_Level  \
0  37-611-6911   22  Female       Middle        Married      Bachelor's
1  29-392-9296   49    Male         High        Married     High School
2  84-649-5117   24  Female       Middle         Single        Master's
3  48-980-6078   29  Female       Middle         Single        Master's
4  91-170-9072   33  Female       Middle        Widowed     High School

  Occupation  Location     Purchase_Category Purchase_Amount  ...  \
0     Middle      Évry  Gardening & Outdoors         $333.80  ...
1       High  Huocheng      Food & Beverages         $222.22  ...
2       High    Huzhen       Office Supplies         $426.22  ...
3     Middle    Wiwilí       Home Appliances         $101.31  ...
4     Middle      Nara             Furniture         $211.70  ...

   Customer_Satisfaction Engagement_with_Ads  Device_Used_for_Shopping  \
0                      7                 NaN                    Tablet
1                      5                High                    Tablet
2                      7                 Low                Smartphone
3                      1                 NaN                Smartphone
4                     10                 NaN                Smartphone

   Payment_Method  Time_of_Purchase Discount_Used  \
0     Credit Card          3/1/2024          True
1          PayPal         4/16/2024          True
2      Debit Card         3/15/2024          True
3           Other         10/4/2024          True
4      Debit Card         1/30/2024         False

  Customer_Loyalty_Program_Member  Purchase_Intent  Shipping_Preference  \
```

```
0                        False      Need-based       No Preference
1                        False     Wants-based            Standard
2                         True       Impulsive       No Preference
3                         True      Need-based             Express
4                        False     Wants-based       No Preference

  Time_to_Decision
0                2
1                6
2                3
3               10
4                4

[5 rows x 28 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 28 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   Customer_ID                            1000 non-null   object
 1   Age                                    1000 non-null   int64
 2   Gender                                 1000 non-null   object
 3   Income_Level                           1000 non-null   object
 4   Marital_Status                         1000 non-null   object
 5   Education_Level                        1000 non-null   object
 6   Occupation                             1000 non-null   object
 7   Location                               1000 non-null   object
 8   Purchase_Category                      1000 non-null   object
 9   Purchase_Amount                        1000 non-null   object
 10  Frequency_of_Purchase                  1000 non-null   int64
 11  Purchase_Channel                       1000 non-null   object
 12  Brand_Loyalty                          1000 non-null   int64
 13  Product_Rating                         1000 non-null   int64
 14  Time_Spent_on_Product_Research(hours)  1000 non-null   float64
 15  Social_Media_Influence                 753 non-null    object
 16  Discount_Sensitivity                   1000 non-null   object
 17  Return_Rate                            1000 non-null   int64
 18  Customer_Satisfaction                  1000 non-null   int64
 19  Engagement_with_Ads                    744 non-null    object
 20  Device_Used_for_Shopping               1000 non-null   object
 21  Payment_Method                         1000 non-null   object
 22  Time_of_Purchase                       1000 non-null   object
 23  Discount_Used                          1000 non-null   bool
 24  Customer_Loyalty_Program_Member        1000 non-null   bool
 25  Purchase_Intent                        1000 non-null   object
 26  Shipping_Preference                    1000 non-null   object
 27  Time_to_Decision                       1000 non-null   int64
dtypes: bool(2), float64(1), int64(7), object(18)
```

```
memory usage: 205.2+ KB
None
```

[75]:
```
df["Social_Media_Influence"] = df["Social_Media_Influence"].fillna("Unknown")
df["Engagement_with_Ads"] = df["Engagement_with_Ads"].fillna("Unknown")
```

[76]:
```
# Missing values are checked for each column
print("Missing values:\n", df.isna().sum())
```

```
Missing values:
 Customer_ID                              0
Age                                      0
Gender                                   0
Income_Level                             0
Marital_Status                           0
Education_Level                          0
Occupation                               0
Location                                 0
Purchase_Category                        0
Purchase_Amount                          0
Frequency_of_Purchase                    0
Purchase_Channel                         0
Brand_Loyalty                            0
Product_Rating                           0
Time_Spent_on_Product_Research(hours)    0
Social_Media_Influence                   0
Discount_Sensitivity                     0
Return_Rate                              0
Customer_Satisfaction                    0
Engagement_with_Ads                      0
Device_Used_for_Shopping                 0
Payment_Method                           0
Time_of_Purchase                         0
Discount_Used                            0
Customer_Loyalty_Program_Member          0
Purchase_Intent                          0
Shipping_Preference                      0
Time_to_Decision                         0
dtype: int64
```

[77]:
```
#the average age of customers for each income level
avg_age_by_income = df.groupby("Income_Level")["Age"].mean()
print(avg_age_by_income)
avg_age_by_income = df.groupby("Income_Level")["Age"].mean()
print(avg_age_by_income)
```

```
Income_Level
High      34.231068
Middle    34.381443
```

```
Name: Age, dtype: float64
Income_Level
High      34.231068
Middle    34.381443
Name: Age, dtype: float64
```

[78]:
```
#the number of customers for each gender
gender_dist = df["Gender"].value_counts()
print(gender_dist)
```

```
Gender
Female         452
Male           449
Bigender        20
Agender         19
Genderfluid     17
Non-binary      16
Polygender      15
Genderqueer     12
Name: count, dtype: int64
```

[79]:
```
#purchase amounts by removing '$' and converting to float
df['Purchase_Amount'] = df['Purchase_Amount'].replace('[\$,]', '', regex=True).
 ↪astype(float)
#the average purchase amount for each category
avg_amount_by_category = df.groupby("Purchase_Category")["Purchase_Amount"].
 ↪mean()
print(avg_amount_by_category.head())
```

```
Purchase_Category
Animal Feed               260.615909
Arts & Crafts             221.468235
Baby Products             272.500488
Beauty & Personal Care    233.676765
Books                     300.613243
Name: Purchase_Amount, dtype: float64
```

[80]:
```
#customers in each marital status category
marital_dist = df["Marital_Status"].value_counts()
print(marital_dist)
```

```
Marital_Status
Widowed     260
Married     253
Divorced    245
Single      242
Name: count, dtype: int64
```

[81]:
```python
#average satisfaction scores per channel
satisfaction_by_channel = df.
 ↪groupby("Purchase_Channel")["Customer_Satisfaction"].mean()
print(satisfaction_by_channel)
```

```
Purchase_Channel
In-Store    5.239264
Mixed       5.379412
Online      5.574850
Name: Customer_Satisfaction, dtype: float64
```

[82]:
```python
#total purchase amounts by device used
total_by_device = df.groupby("Device_Used_for_Shopping")["Purchase_Amount"].sum()
print(total_by_device)
```

```
Device_Used_for_Shopping
Desktop       93344.49
Smartphone    87717.59
Tablet        94001.80
Name: Purchase_Amount, dtype: float64
```

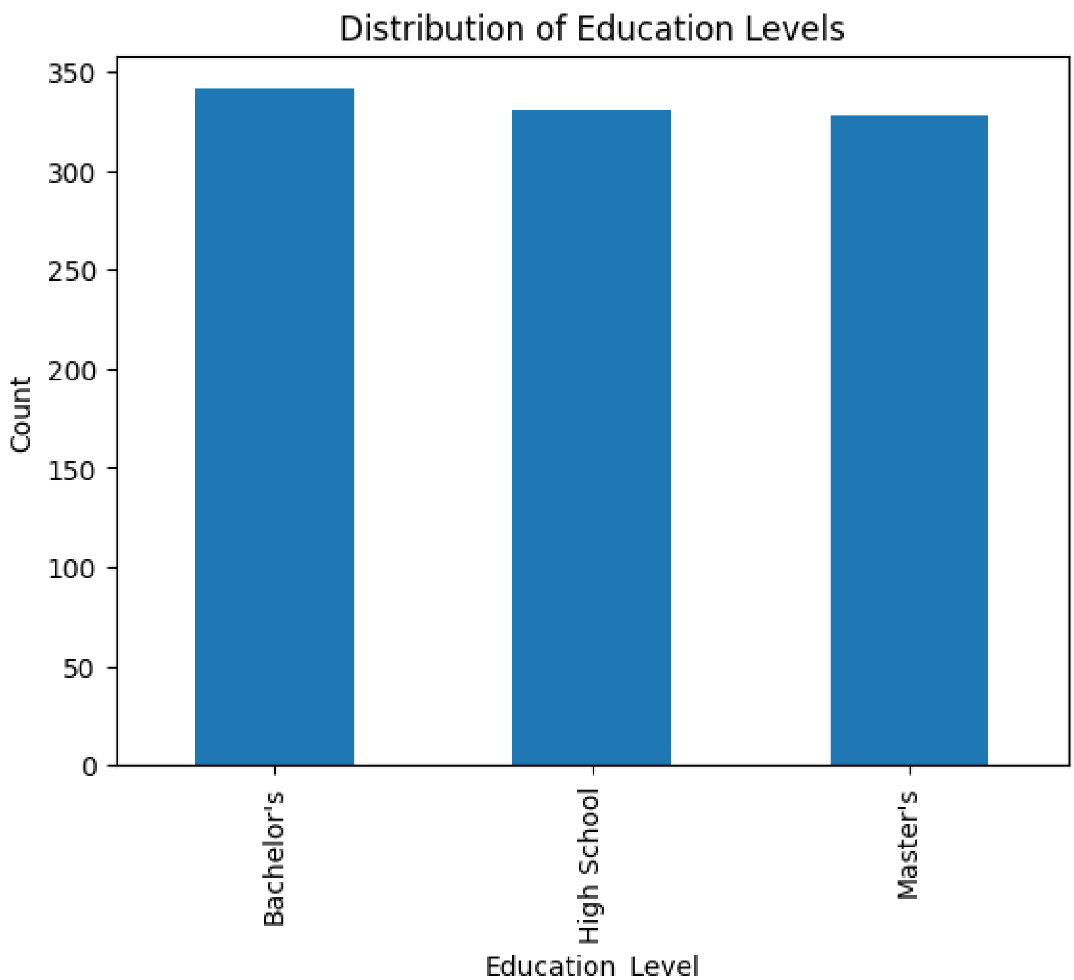
[83]:
```python
#the top 5 purchase categories with the highest total spending
top_categories = df.groupby("Purchase_Category")["Purchase_Amount"].sum().
 ↪nlargest(5)
print(top_categories)
```

```
Purchase_Category
Jewelry & Accessories    15139.36
Sports & Outdoors        14610.51
Electronics              13842.41
Software & Apps          13601.41
Toys & Games             13536.46
Name: Purchase_Amount, dtype: float64
```

[84]:
```python
#Compare average purchase amount between loyalty members vs non-members
loyalty_by_amount = df.
 ↪groupby("Customer_Loyalty_Program_Member")["Purchase_Amount"].mean()
print(loyalty_by_amount)
```

```
Customer_Loyalty_Program_Member
False    288.373026
True     261.266823
Name: Purchase_Amount, dtype: float64
```

[85]:
```
df["Education_Level"].value_counts().plot(kind="bar")
plt.title("Distribution of Education Levels")
plt.ylabel("Count")
plt.show()
```



[86]:
```
#average research time per age
research_by_age = df.groupby("Age")["Time_Spent_on_Product_Research(hours)"].
    ↪mean()
print(research_by_age.head())
```

```
Age
18      1.230000
19      0.921875
20      0.710526
21      1.109429
22      0.973684
```

```
Name: Time_Spent_on_Product_Research(hours), dtype: float64
```

[87]:
```python
#percentage of discount usage by gender
discount_by_gender = df.groupby("Gender")["Discount_Used"].
 ↪value_counts(normalize=True) * 100
print(discount_by_gender.head())
```

```
Gender    Discount_Used
Agender   True             68.421053
          False            31.578947
Bigender  False            55.000000
          True             45.000000
Female    True             53.097345
Name: proportion, dtype: float64
```

[88]:
```python
#the average satisfaction scores for each income level
satisfaction_by_income = df.groupby("Income_Level")["Customer_Satisfaction"].
 ↪mean()
print(satisfaction_by_income)
```

```
Income_Level
High      5.207767
Middle    5.602062
Name: Customer_Satisfaction, dtype: float64
```

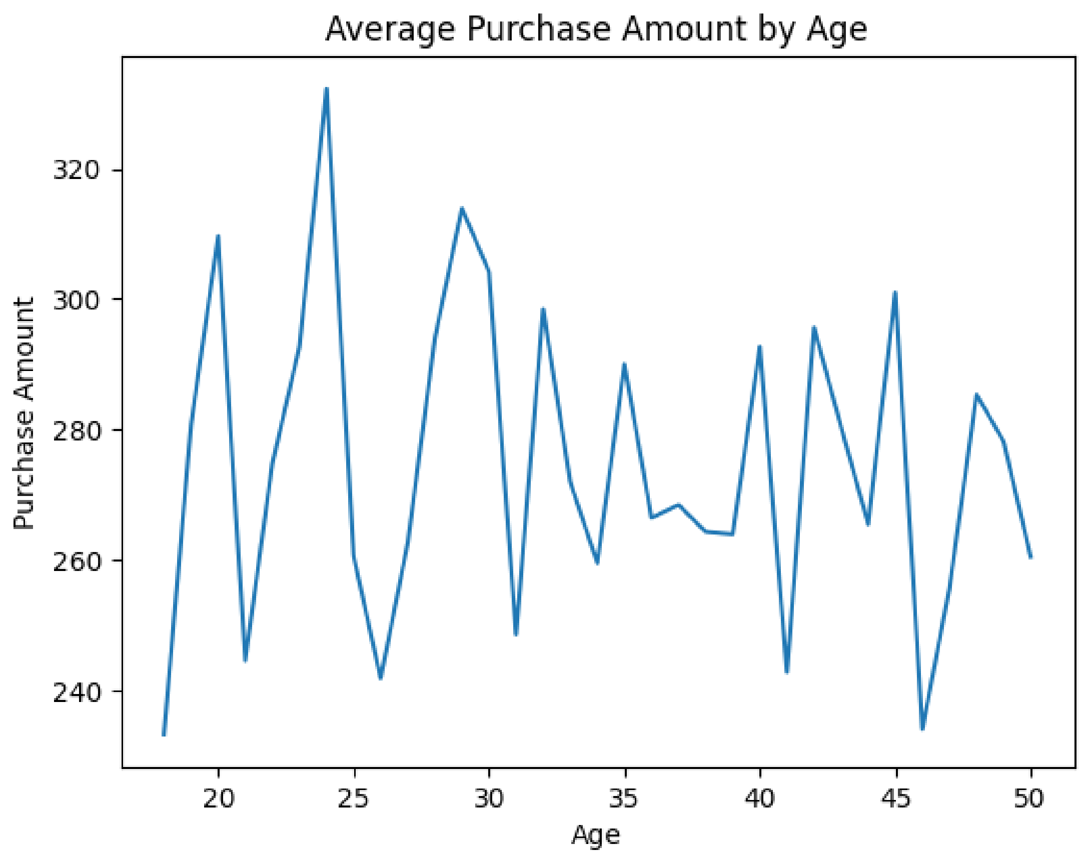
[89]:
```python
#average time taken to make purchase decisions per category
decision_by_category = df.groupby("Purchase_Category")["Time_to_Decision"].mean()
print(decision_by_category.head())
```

```
Purchase_Category
Animal Feed               7.818182
Arts & Crafts             8.058824
Baby Products             7.536585
Beauty & Personal Care    8.382353
Books                     8.189189
Name: Time_to_Decision, dtype: float64
```

[90]:
```python
# Group customers into age bins and count how many fall into each
age_bins = pd.cut(df["Age"], bins=[0, 30, 50, 70, 100])
age_dist = df.groupby(age_bins, observed=False)["Customer_ID"].count()
print(age_dist)
```

```
Age
(0, 30]      387
(30, 50]     613
(50, 70]       0
(70, 100]      0
Name: Customer_ID, dtype: int64
```

[91]:
```
df.groupby("Age")["Purchase_Amount"].mean().plot(kind="line")
plt.title("Average Purchase Amount by Age")
plt.ylabel("Purchase Amount")
plt.show()
```



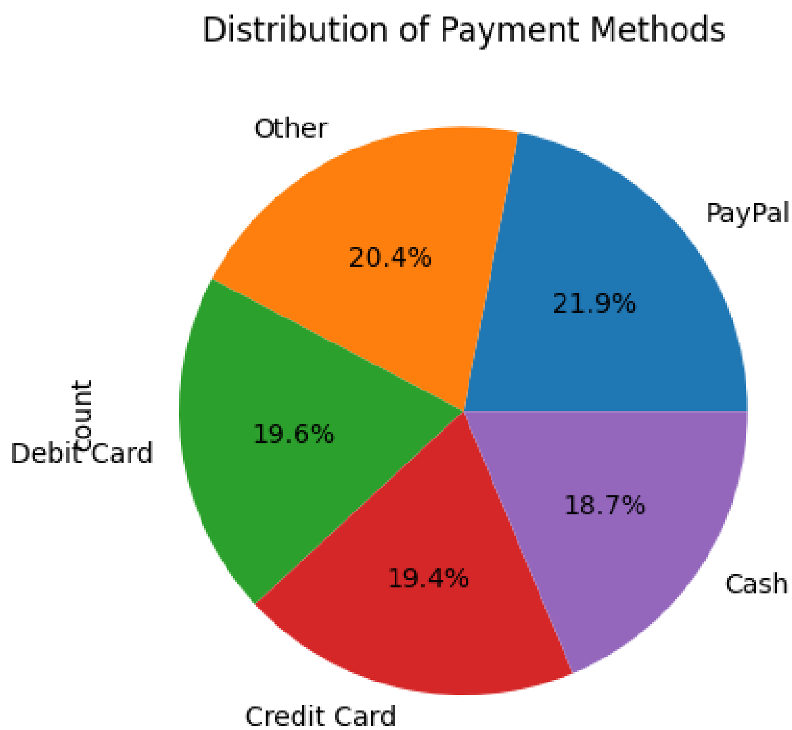
[92]:
```
#Compare average purchase amount based on ad engagement
ads_by_amount = df.groupby("Engagement_with_Ads")["Purchase_Amount"].mean()
print(ads_by_amount)
```

```
Engagement_with_Ads
High       277.658222
Low        268.259522
Medium     281.211107
Unknown    272.581875
Name: Purchase_Amount, dtype: float64
```

[93]:
```
total_by_payment = df.groupby("Payment_Method")["Purchase_Amount"].sum()
print(total_by_payment)
```

```
Payment_Method
Cash           50072.47
Credit Card    52677.54
Debit Card     53552.04
Other          57797.50
PayPal         60964.33
Name: Purchase_Amount, dtype: float64
```

[94]:
```
df["Payment_Method"].value_counts().plot(kind="pie", autopct='%1.1f%%')
plt.title("Distribution of Payment Methods")
plt.show()
```



[95]:
```
#how purchase intent varies by gender
intent_by_gender = df.groupby("Gender")["Purchase_Intent"].value_counts()
print(intent_by_gender.head())
```

```
Gender     Purchase_Intent
Agender    Need-based         6
           Planned            5
           Wants-based        5
```

```
          Impulsive         3
Bigender  Need-based        7
Name: count, dtype: int64
```

[96]:
```python
#how social media influence affects purchase intent
influence_by_intent = df.groupby("Social_Media_Influence")["Purchase_Intent"].
 ↪value_counts()
print(influence_by_intent.head())
```

```
Social_Media_Influence  Purchase_Intent
High                    Impulsive          73
                        Wants-based        73
                        Need-based         66
                        Planned            56
Low                     Planned            72
Name: count, dtype: int64
```

[97]:
```python
#the number of customers per purchase channel
channel_dist = df["Purchase_Channel"].value_counts()
print(channel_dist)
```

```
Purchase_Channel
Mixed       340
Online      334
In-Store    326
Name: count, dtype: int64
```

[98]:
```python
#how satisfaction varies depending on purchase intent
satisfaction_by_intent = df.groupby("Purchase_Intent")["Customer_Satisfaction"].
 ↪mean()
print(satisfaction_by_intent)
```

```
Purchase_Intent
Impulsive      5.395161
Need-based     5.375000
Planned        5.230769
Wants-based    5.594378
Name: Customer_Satisfaction, dtype: float64
```

[99]:
```python
#average purchase amount with and without discount use
discount_by_amount = df.groupby("Discount_Used")["Purchase_Amount"].mean()
print(discount_by_amount)
```

```
Discount_Used
False    276.229436
True     273.992284
Name: Purchase_Amount, dtype: float64
```

[100]:

```python
#total spending by customers in each occupation
total_by_occupation = df.groupby("Occupation")["Purchase_Amount"].sum()
print(total_by_occupation)
```

```
Occupation
High      140776.67
Middle    134287.21
Name: Purchase_Amount, dtype: float64
```

[101]:

```python
#the top 10 customers with the highest total purchase spending
top_customers = df.groupby("Customer_ID")["Purchase_Amount"].sum().nlargest(10)
print(top_customers)
```

```
Customer_ID
60-470-3563    498.33
13-848-5757    498.23
15-663-7994    497.80
86-257-9581    497.76
15-421-1255    497.75
72-830-1211    496.11
85-467-6564    495.95
72-590-6161    495.80
69-394-1424    494.97
59-261-4453    494.81
Name: Purchase_Amount, dtype: float64
```

[102]:
```
pivot = df.pivot_table(values="Purchase_Amount", index="Customer_Satisfaction",␣
↪aggfunc="mean")
sns.heatmap(pivot)
plt.title("Purchase Amount vs Customer Satisfaction")
plt.show()
```

[103]:
```
#Identify the 10 locations with the highest total purchase amount
top_locations = df.groupby("Location")["Purchase_Amount"].sum().nlargest(10)
print(top_locations)
```

```
Location
Göteborg          1161.29
Oslo              1021.55
Punta Gorda        820.45
Magdalena          804.74
Hoolt              780.60
Veiga              779.89
San Carlos         722.39
Týn nad Vltavou    682.59
Cimara             673.61
Seleuš             672.99
```

```
Name: Purchase_Amount, dtype: float64
```

[104]:

```
plt.figure(figsize=(10, 6))
top_locations.plot(kind="bar")
plt.title("Top 10 Locations by Total Purchase Amount")
plt.xlabel("Location")
plt.ylabel("Total Purchase Amount")
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```