CS 4048 – Data Science

Final Project

Introduction

Imtiaz Mall, a renowned department store chain, is experiencing declining sales and a significant number of non-recurring customers in its electronics section. To address this challenge, you, the newly appointed Senior Data Scientist, have been tasked with conducting a comprehensive analysis of the electronics section data and developing data-driven strategies for customer retention and sales growth. This project focuses on the initial steps of this analysis, specifically exploring the data through various techniques and comparing the results of three clustering algorithms: K-Means, DBSCAN, and K-Means++.

Module : Data Acquisition and Preprocessing

1. Data Acquisition:

First of all we import the libraries such as pandas, json, numpy and read data from file.

In [280]:

```
import pandas as pd
import json
import numpy as np


df = pd.read_json('electronics.json')
df
```

Out[280]:

	Customer_ID	Age	Gender	Income_Level	Address	Transaction_ID	Purchase_Date	Product_ID	Product_Category	Brand	Purc
0	b81ee6c9-2ae4-48a7-b283-220eaa244f43	40	Female	Medium	43548 Murray Islands Suite 974\nAmyberg, CT 13457	c6a6c712-e36b-406a-bfde-f53bdcf4744f	2022-04-26	d2f767d6-b01a-41a2-87f7-ec1d1186f50e	Clothing	Brand_C	
1		25	Male	High		0b587838-1e4f-4231-b488-42bcd47c052a	2021-08-10	79eadc55-2de1-41cf-b1b6-40118c0bf8ec	Books	Brand_A	
2	fdf79bcd-5908-4c90-8501-570ffb5b7648	57	Other	Low	79683 Kevin Hill Apt. 555\nJohnshire, AR 39961	462925b1-a5bf-4996-bda2-59749de64eea	2021-12-09	9ab75a68-4329-4bd9-a259-2233c0f34c93	Electronics	Brand_A	
3	878dccba-893a-48f9-8d34-6ed394fa3c9c	38	Female	Medium	02998 Hall Meadows Suite 809\nNorth Robertvill...	3cfafa02-6b34-4d77-9e05-d223dfab64e8	2022-12-03	d518569b-ff79-494b-b2b6-7e2af39db86a	Clothing	Brand_C	
4	0af0bd81-73cc-494e-aa5e-75c6d0b6d743	68	Other	Medium	21411 Timothy Ford Apt. 320\nDavisborough, AR ...	0d8dc27a-0c8f-4a82-b57e-8bf54cee9759	2020-06-08	b6deac9d-2b7e-4a51-8273-a6534910b3bc	Books	Brand_B	
...	...	...	...	...	...	...	...	...	...	...	
995		70	Male	Medium	566 Butler Turnpike\nPort Holly, OK 22329	776be313-5308-468e-a0ed-7409a4303364	2023-03-17	1802f115-80d8-48fd-ad97-94038fe31b82	Electronics	Brand_C	
996	2116266d-8d1c-48cc-ac28-e4e675cb2a4d	78	Female	Low	45710 Wilson Circles Apt. 411\nWalterton, NC 8...	51f771bf-2562-46c1-a25d-2f46f4bb1525	2023-08-30	546d8d8f-1498-4aa9-8123-29550d911a17	Books	Brand_B	
997	562cee08-f909-4e1c-a811-5711f967bea5	63	Male	High	243 Emily Creek\nSouth Lindaport, CO 81594	74eba598-ee91-4396-a137-6b869702ef29	Hidden	8b6ffec8-de54-445c-90d0-1399858b2e16	Hidden	Brand_C	
998	84da2eea-6e9e-46d4-8d94-1e9b0c377d78	43	Male	High	1129 Kirby Ferry Suite 743\nBillyfurt, UT 41587	4d2e213e-bcc0-4a8a-9501-6ca8361381c4	2021-05-13	51ed2d86-c9ab-4922-a8ff-469acf6ac91e	Clothing	Brand_C	
999	87629baf-a138-4374-be37-8bab776379b8	19	Other	High	896 Troy Branch\nAmytown, NJ 62321	69afa592-2658-48ac-9b37-33a3a473d0be	2022-09-13	91ba2109-15aa-40a0-aa9c-732a1e2e1e27	Clothing	Brand_B	

1000 rows × 18 columns

2. Data Cleaning:

The data cleaning process involves several key steps to ensure the reliability and consistency of the dataset. Now we start data cleaning process we have dataset which have some empty values and Hidden values in data. First we replace hidden values in data with NAN. and then we replace empty values with NAN.

In [281]:
```
df.replace('Hidden', np.nan, inplace=True)
df.replace("", np.nan, inplace=True)
df
```

Out[281]:

	Customer_ID	Age	Gender	Income_Level	Address	Transaction_ID	Purchase_Date	Product_ID	Product_Category	Brand	Purc
0	b81ee6c9-2ae4-48a7-b283-220eaa244f43	40	Female	Medium	43548 Murray Islands Suite 974\nAmyberg, CT 13457	c6a6c712-e36b-406a-bfde-f53bdcf4744f	2022-04-26	d2f767d6-b01a-41a2-87f7-ec1d1186f50e	Clothing	Brand_C	
1	NaN	25	Male	High	NaN	0b587838-1e4f-4231-b488-42bcd47c052a	2021-08-10	79eadc55-2de1-41cf-b1b6-40118c0bf8ec	Books	Brand_A	
2	fdf79bcd-5908-4c90-8501-570ffb5b7648	57	Other	Low	79683 Kevin Hill Apt. 555\nJohnshire, AR 39961	462925b1-a5bf-4996-bda2-59749de64eea	2021-12-09	9ab75a68-4329-4bd9-a259-2233c0f34c93	Electronics	Brand_A	
3	878dccba-893a-48f9-8d34-6ed394fa3c9c	38	Female	Medium	02998 Hall Meadows Suite 809\nNorth Robertvill...	3cfafa02-6b34-4d77-9e05-d223dfab64e8	2022-12-03	d518569b-ff79-494b-b2b6-7e2af39db86a	Clothing	Brand_C	
4	0af0bd81-73cc-494e-aa5e-75c6d0b6d743	68	Other	Medium	21411 Timothy Ford Apt. 320\nDavisborough, AR ...	0d8dc27a-0c8f-4a82-b57e-8bf54cee9759	2020-06-08	b6deac9d-2b7e-4a51-8273-a6534910b3bc	Books	Brand_B	
...	...	...	...	...	...	...	...	...	...	...	
995	NaN	70	Male	Medium	566 Butler Turnpike\nPort Holly, OK 22329	776be313-5308-468e-a0ed-7409a4303364	2023-03-17	1802f115-80d8-48fd-ad97-94038fe31b82	Electronics	Brand_C	
996	2116266d-8d1c-48cc-ac28-e4e675cb2a4d	78	Female	Low	45710 Wilson Circles Apt. 411\nWalterton, NC 8...	51f771bf-2562-46c1-a25d-2f46f4bb1525	2023-08-30	546d8d8f-1498-4aa9-8123-29550d911a17	Books	Brand_B	
997	562cee08-f909-4e1c-a811-5711f967bea5	63	Male	High	243 Emily Creek\nSouth Lindaport, CO 81594	74eba598-ee91-4396-a137-6b869702ef29	NaN	8b6ffec8-de54-445c-90d0-1399858b2e16	NaN	Brand_C	
998	84da2eea-6e9e-46d4-8d94-1e9b0c377d78	43	Male	High	1129 Kirby Ferry Suite 743\nBillyfurt, UT 41587	4d2e213e-bcc0-4a8a-9501-6ca8361381c4	2021-05-13	51ed2d86-c9ab-4922-a8ff-469acf6ac91e	Clothing	Brand_C	
999	87629baf-a138-4374-be37-8bab776379b8	19	Other	High	896 Troy Branch\nAmytown, NJ 62321	69afa592-2658-48ac-9b37-33a3a473d0be	2022-09-13	91ba2109-15aa-40a0-aa9c-732a1e2e1e27	Clothing	Brand_B	

1000 rows × 18 columns

Now we check the total null values in all columns

In [282]:
```
null_values_count = df.isnull().sum()

print("Null Values per Column:")
print(null_values_count)
```

```
Null Values per Column:
Customer_ID                     44
Age                             40
Gender                          48
Income_Level                    50
Address                         47
Transaction_ID                  50
Purchase_Date                   48
Product_ID                      49
Product_Category                60
Brand                           58
Purchase_Amount                 49
Average_Spending_Per_Purchase   40
Purchase_Frequency_Per_Month    55
Brand_Affinity_Score            61
Product_Category_Preferences    43
Month                           53
Year                            52
Season                          48
dtype: int64
```

In [283]:
```
df['Age'] = pd.to_numeric(df['Age'], errors='coerce')

mean_age = df['Age'].mean()

df['Age'] = df['Age'].fillna(round(mean_age)).astype(int)
```

In [284]:
```
mode_inc = df['Income_Level'].mode()[0]
df['Income_Level'].fillna(mode_inc, inplace=True)


mode_inc = df['Gender'].mode()[0]
df['Gender'].fillna(mode_inc, inplace=True)
```

In [285]:
```
mode_add = df['Address'].mode()[0]
df['Address'].fillna(mode_add, inplace=True)
```

In [286]:
```
mode_pr = df['Purchase_Date'].mode()[0]
df['Purchase_Date'].fillna(mode_pr, inplace=True)
```

In [287]:
```
mode_Product_Category = df['Product_Category'].mode()[0]
df['Product_Category'].fillna(mode_Product_Category, inplace=True)
```

In [288]:
```
mode_Brand  = df['Brand'].mode()[0]
df['Brand'].fillna(mode_Brand , inplace=True)
```

In [289]:
```
df['Purchase_Amount'] = pd.to_numeric(df['Purchase_Amount'], errors='coerce')
mean_purchase_amount = df['Purchase_Amount'].mean()
df['Purchase_Amount'].fillna(mean_purchase_amount, inplace=True)
df['Purchase_Amount'] = df['Purchase_Amount'].astype(int)
```

In [290]:
```
df['Average_Spending_Per_Purchase'] = pd.to_numeric(df['Average_Spending_Per_Purchase'], errors='coerce')
mean_purchase_amount = df['Average_Spending_Per_Purchase'].mean()
df['Average_Spending_Per_Purchase'].fillna(mean_purchase_amount, inplace=True)
df['Average_Spending_Per_Purchase'] = df['Average_Spending_Per_Purchase'].astype(int)
```

In [291]:
```
df['Purchase_Frequency_Per_Month'] = pd.to_numeric(df['Purchase_Frequency_Per_Month'], errors='coerce')

median_Purchase_Frequency_Per_Month = df['Purchase_Frequency_Per_Month'].mean()
df['Purchase_Frequency_Per_Month'].fillna(median_Purchase_Frequency_Per_Month, inplace=True)

df['Purchase_Frequency_Per_Month'] = df['Purchase_Frequency_Per_Month'].astype(int)
```

In [292]:
```
df['Brand_Affinity_Score'] = pd.to_numeric(df['Brand_Affinity_Score'], errors='coerce')

median_brand_affinity_score = df['Brand_Affinity_Score'].mean()
df['Brand_Affinity_Score'].fillna(median_brand_affinity_score, inplace=True)

df['Brand_Affinity_Score'] = df['Brand_Affinity_Score'].astype(int)
```

In [293]:
```
mode_product_category = df['Product_Category_Preferences'].mode()[0]
df['Product_Category_Preferences'].fillna(mode_product_category, inplace=True)
```

In [294]:
```
mode_month = df['Month'].mode()[0]
mode_year = df['Year'].mode()[0]
mode_season = df['Season'].mode()[0]
mode_cus = df['Customer_ID'].mode()[0]
mode_trans = df['Transaction_ID'].mode()[0]
mode_product = df['Product_ID'].mode()[0]


df['Month'].fillna(mode_month, inplace=True)
df['Year'].fillna(mode_year, inplace=True)
df['Season'].fillna(mode_season, inplace=True)
df['Customer_ID'].fillna(mode_cus, inplace=True)
df['Transaction_ID'].fillna(mode_trans, inplace=True)
df['Product_ID'].fillna(mode_product, inplace=True)
```

In [295]:
```
# Analyze outliers in 'Age' column
Q1_age = df['Age'].quantile(0.25)
Q3_age = df['Age'].quantile(0.75)
IQR_age = Q3_age - Q1_age

lower_bound_age = Q1_age - 1.5 * IQR_age
upper_bound_age = Q3_age + 1.5 * IQR_age

outliers_age = df[(df['Age'] < lower_bound_age) | (df['Age'] > upper_bound_age)]
print("Potential Outliers in 'Age' column:")
print(outliers_age[['Age']])
```

```
Potential Outliers in 'Age' column:
Empty DataFrame
Columns: [Age]
Index: []
```

In [296]:
```
# Analyze outliers in 'Purchase_Amount' column
Q1_purchase = df['Purchase_Amount'].quantile(0.25)
Q3_purchase = df['Purchase_Amount'].quantile(0.75)
IQR_purchase = Q3_purchase - Q1_purchase

lower_bound_purchase = Q1_purchase - 1.5 * IQR_purchase
upper_bound_purchase = Q3_purchase + 1.5 * IQR_purchase

outliers_purchase = df[(df['Purchase_Amount'] < lower_bound_purchase) | (df['Purchase_Amount'] > upper_bound_purchase)]
print("\nPotential Outliers in 'Purchase_Amount' column:")
print(outliers_purchase[['Purchase_Amount']])
```

```
Potential Outliers in 'Purchase_Amount' column:
Empty DataFrame
Columns: [Purchase_Amount]
Index: []
```

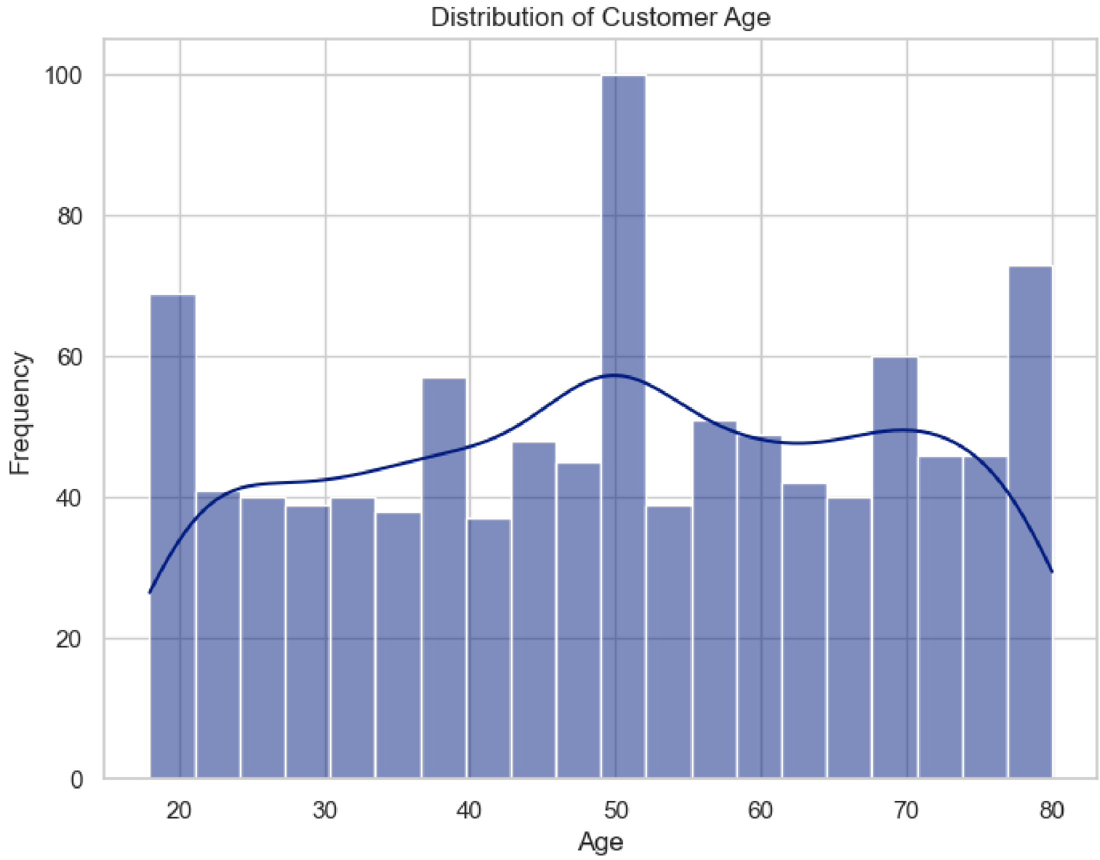
In [297]:
```
#Description: Represents the total spending of each customer, taking into account both the purchase amount and frequency.
df['Total_Spending'] = df['Purchase_Amount'] * df['Purchase_Frequency_Per_Month']


#Combines information about the preferred brand and product category for each customer.
df['Preferred_Brand_Category'] = df['Brand'] + '_' + df['Product_Category']

#Identifies customers with significantly higher than average spending. Binary indicator (1 for high spender, 0 otherwise).
average_spending = df['Purchase_Amount'].mean()
df['High_Spending_Customers'] = (df['Purchase_Amount'] > average_spending).astype(int)
```

In [298]:
```
df.info()
```

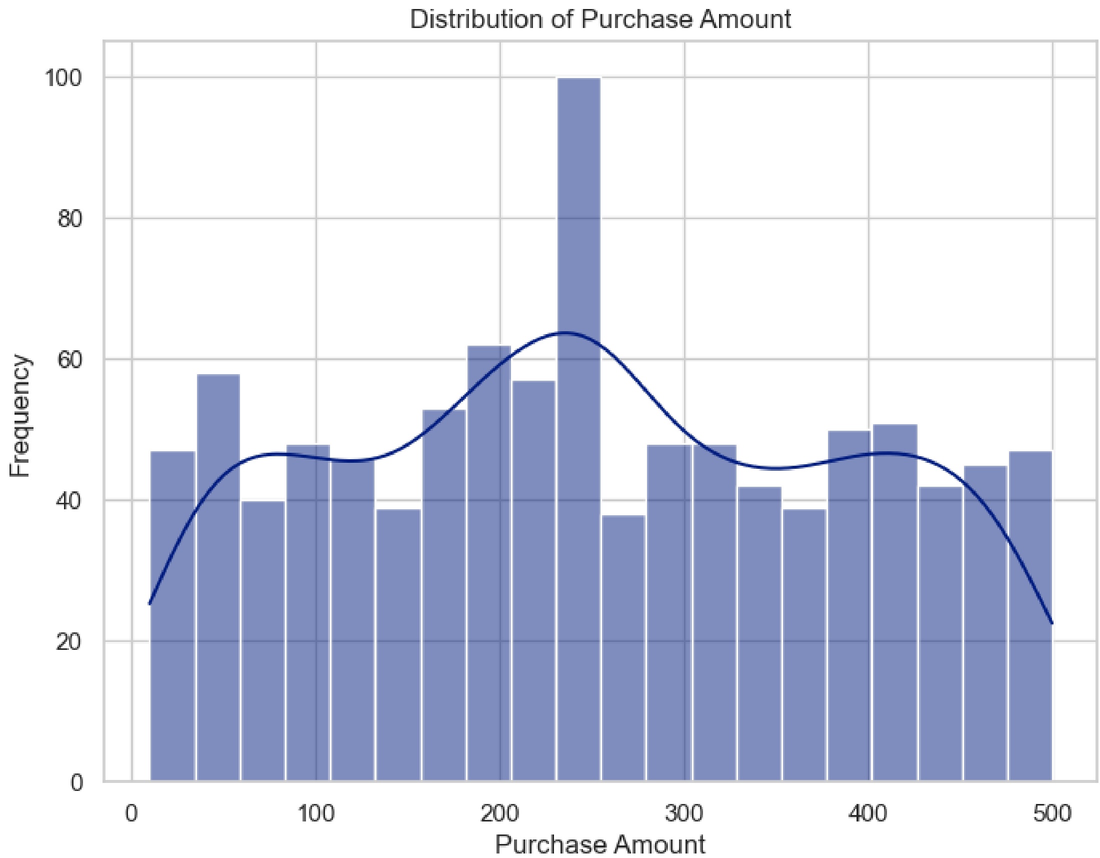
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Customer_ID                    1000 non-null   object
 1   Age                            1000 non-null   int32
 2   Gender                         1000 non-null   object
 3   Income_Level                   1000 non-null   object
 4   Address                        1000 non-null   object
 5   Transaction_ID                 1000 non-null   object
 6   Purchase_Date                  1000 non-null   object
 7   Product_ID                     1000 non-null   object
 8   Product_Category               1000 non-null   object
 9   Brand                          1000 non-null   object
 10  Purchase_Amount                1000 non-null   int32
 11  Average_Spending_Per_Purchase  1000 non-null   int32
 12  Purchase_Frequency_Per_Month   1000 non-null   int32
 13  Brand_Affinity_Score           1000 non-null   int32
 14  Product_Category_Preferences   1000 non-null   object
 15  Month                          1000 non-null   object
 16  Year                           1000 non-null   object
 17  Season                         1000 non-null   object
 18  Total_Spending                 1000 non-null   int32
 19  Preferred_Brand_Category       1000 non-null   object
 20  High_Spending_Customers        1000 non-null   int32
dtypes: int32(7), object(14)
memory usage: 136.8+ KB
```

In [299]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Set the style and color palette
sns.set(style="whitegrid", palette="dark")

# Histogram for customer age
plt.figure(figsize=(8, 6))
sns.histplot(df['Age'], bins=20, kde=True)
plt.title('Distribution of Customer Age')
```

```
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```

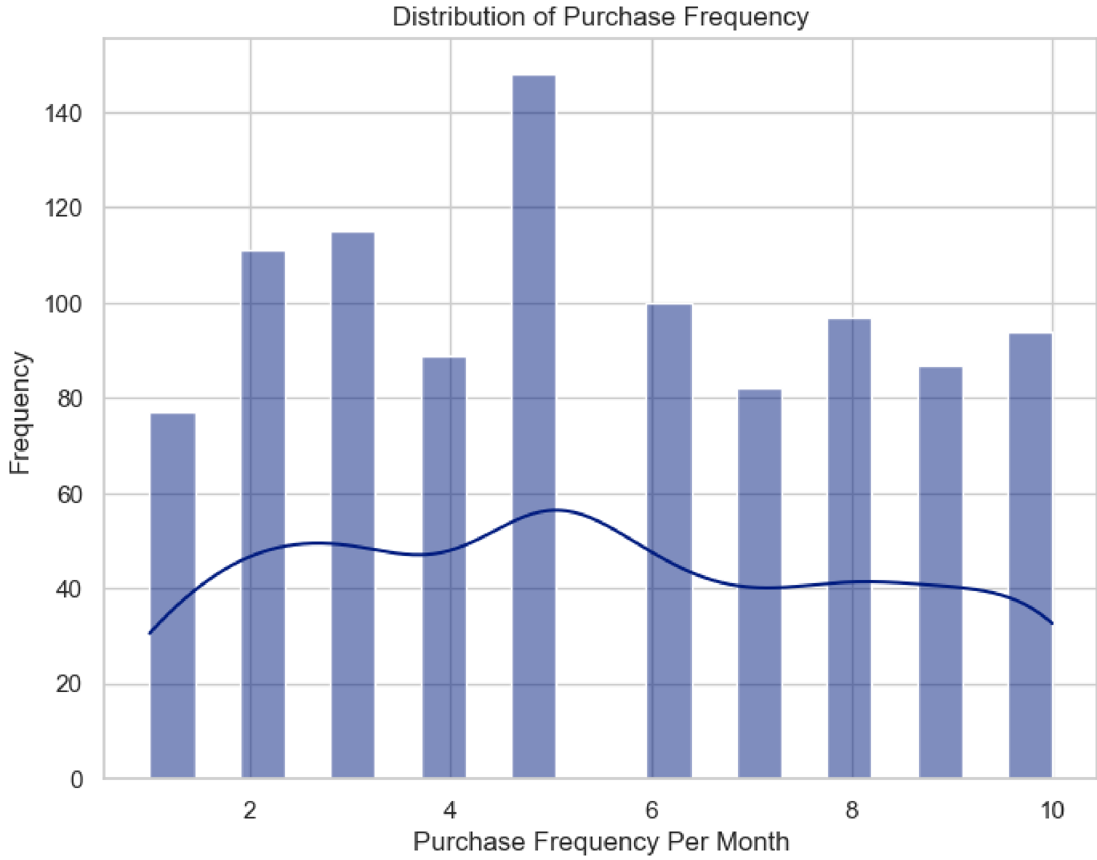


In [300]:
```
# Histogram for purchase amount
plt.figure(figsize=(8, 6))
sns.histplot(df['Purchase_Amount'], bins=20, kde=True)
plt.title('Distribution of Purchase Amount')
plt.xlabel('Purchase Amount')
plt.ylabel('Frequency')
plt.show()
```

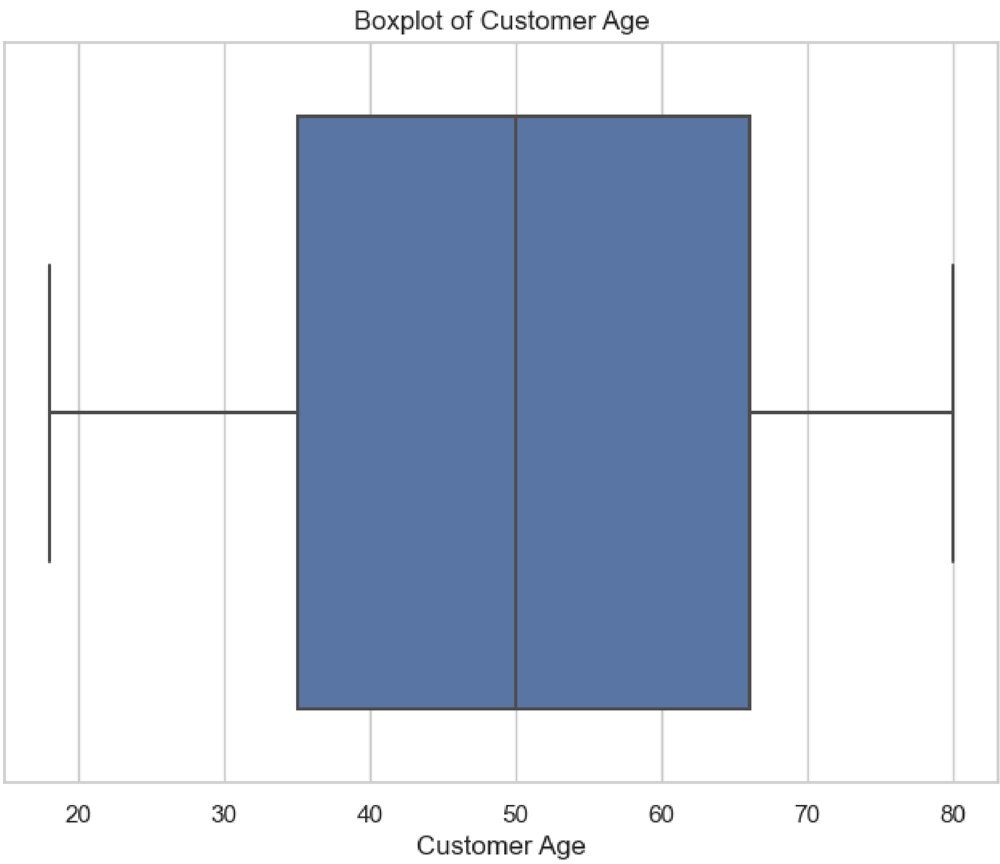


In [301]:
```
# Histogram for purchase frequency
plt.figure(figsize=(8, 6))
sns.histplot(df['Purchase_Frequency_Per_Month'], bins=20, kde=True)
plt.title('Distribution of Purchase Frequency')
plt.xlabel('Purchase Frequency Per Month')
```

```
plt.ylabel('Frequency')
plt.show()
```

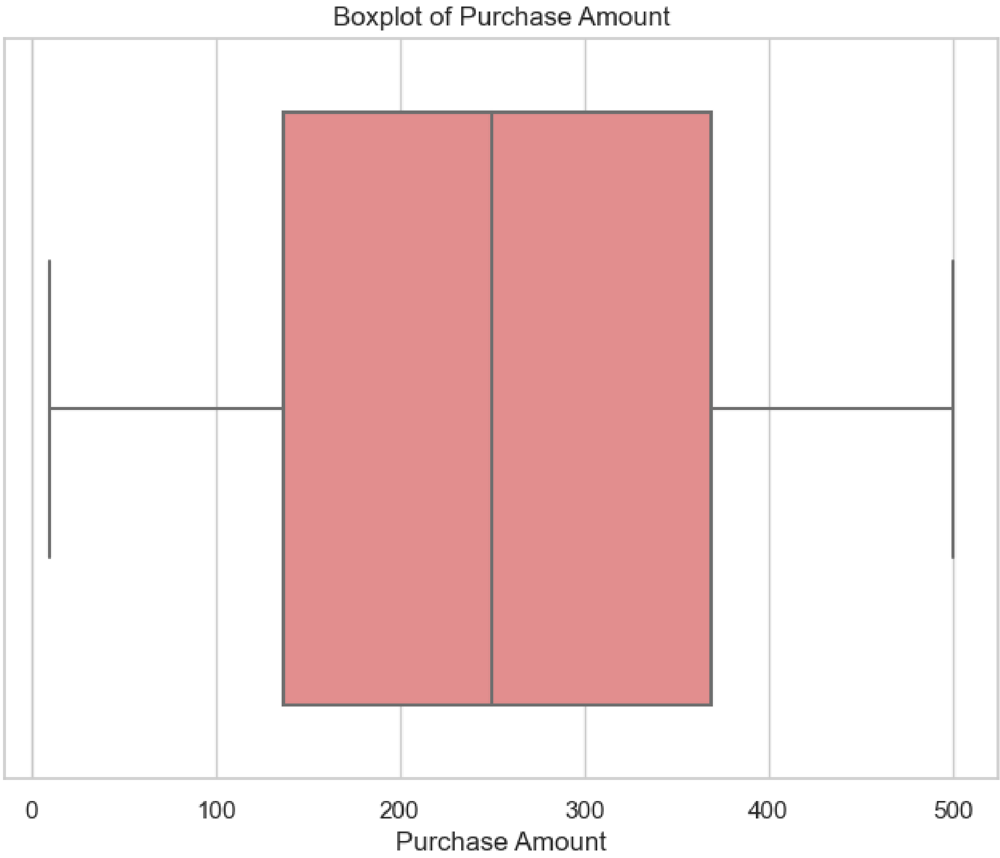


In [302]:
```
# Set the style and color palette
sns.set(style="whitegrid", palette="deep")

# Boxplot for customer age
plt.figure(figsize=(8, 6))
sns.boxplot(x=df['Age'])
plt.title('Boxplot of Customer Age')
plt.xlabel('Customer Age')
plt.show()
```



In [303]:
```
# 2. Boxplot for Purchase Amount
plt.figure(figsize=(8, 6))
sns.boxplot(x=df['Purchase_Amount'], color='lightcoral')
plt.title('Boxplot of Purchase Amount')
```

```
plt.xlabel('Purchase Amount')
plt.show()
```



In [304]:
```
# Boxplot for purchase amount wrt seasons
plt.figure(figsize=(8, 6))
sns.boxplot(x='Season', y='Purchase_Amount', data=df)
plt.title('Boxplot of Purchase Amount')
plt.xlabel('Purchase Amount')
plt.show()
```

In [305]:
```
import pandas as pd
import plotly.express as px


age_bins = [0, 20, 30, 40, 50, 60, 70, 80, 90, 100]
age_labels = ['0-20', '21-30', '31-40', '41-50', '51-60', '61-70', '71-80', '81-90', '91-100']
```

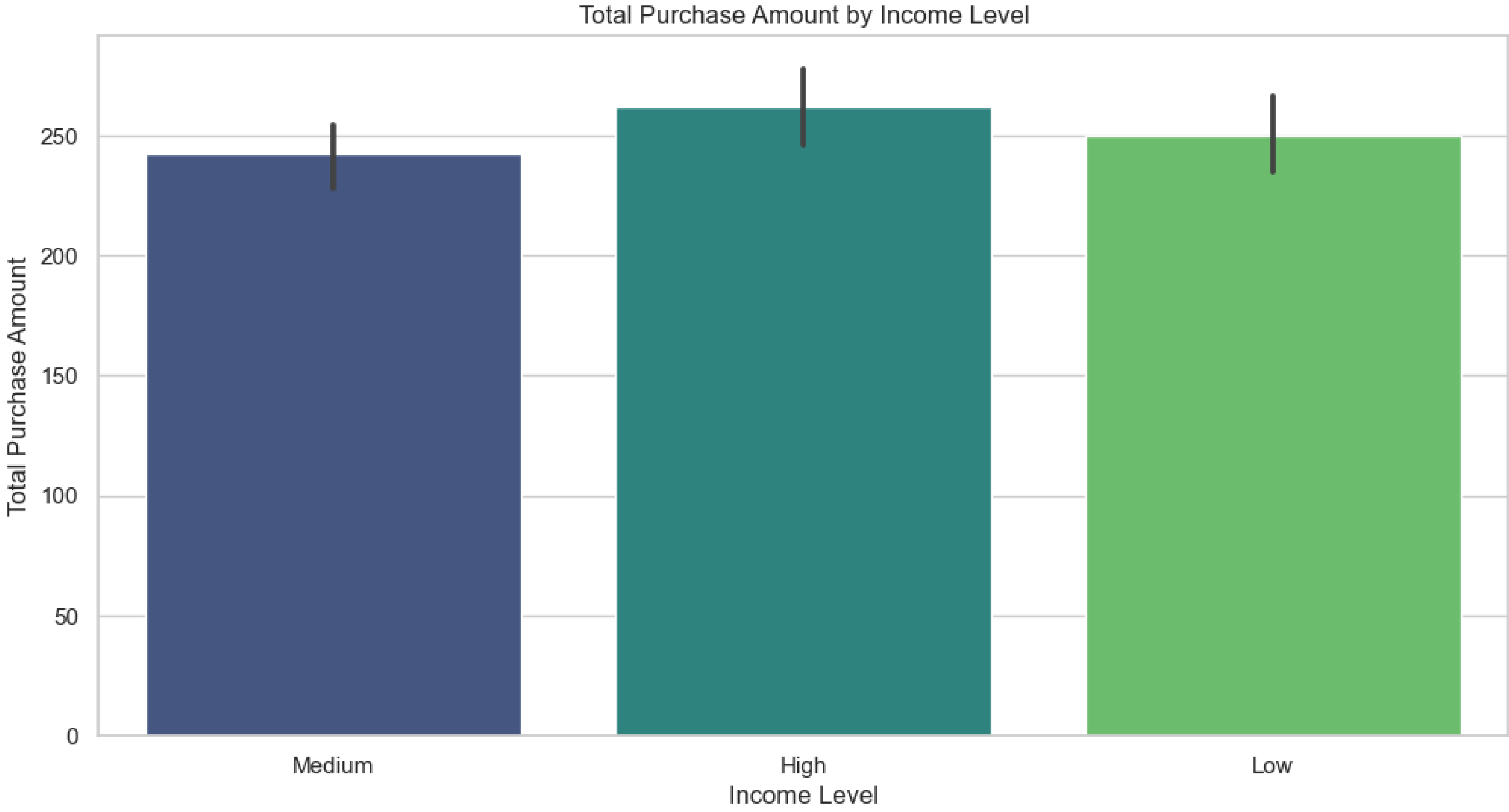
```
df['Age_Group'] = pd.cut(df['Age'], bins=age_bins, labels=age_labels, right=False)


age_group_stats = df.groupby('Age_Group').agg({
    'Purchase_Amount': 'sum',
    'Average_Spending_Per_Purchase': 'mean',
    'Purchase_Frequency_Per_Month': 'sum'
}).reset_index()



plt.figure(figsize=(8, 6))
sns.set(style="whitegrid", palette="pastel")
fig = px.bar(age_group_stats, x='Age_Group', y='Purchase_Amount', title='Total Purchase Amount by Age Group')
fig.show()
```

<Figure size 800x600 with 0 Axes>

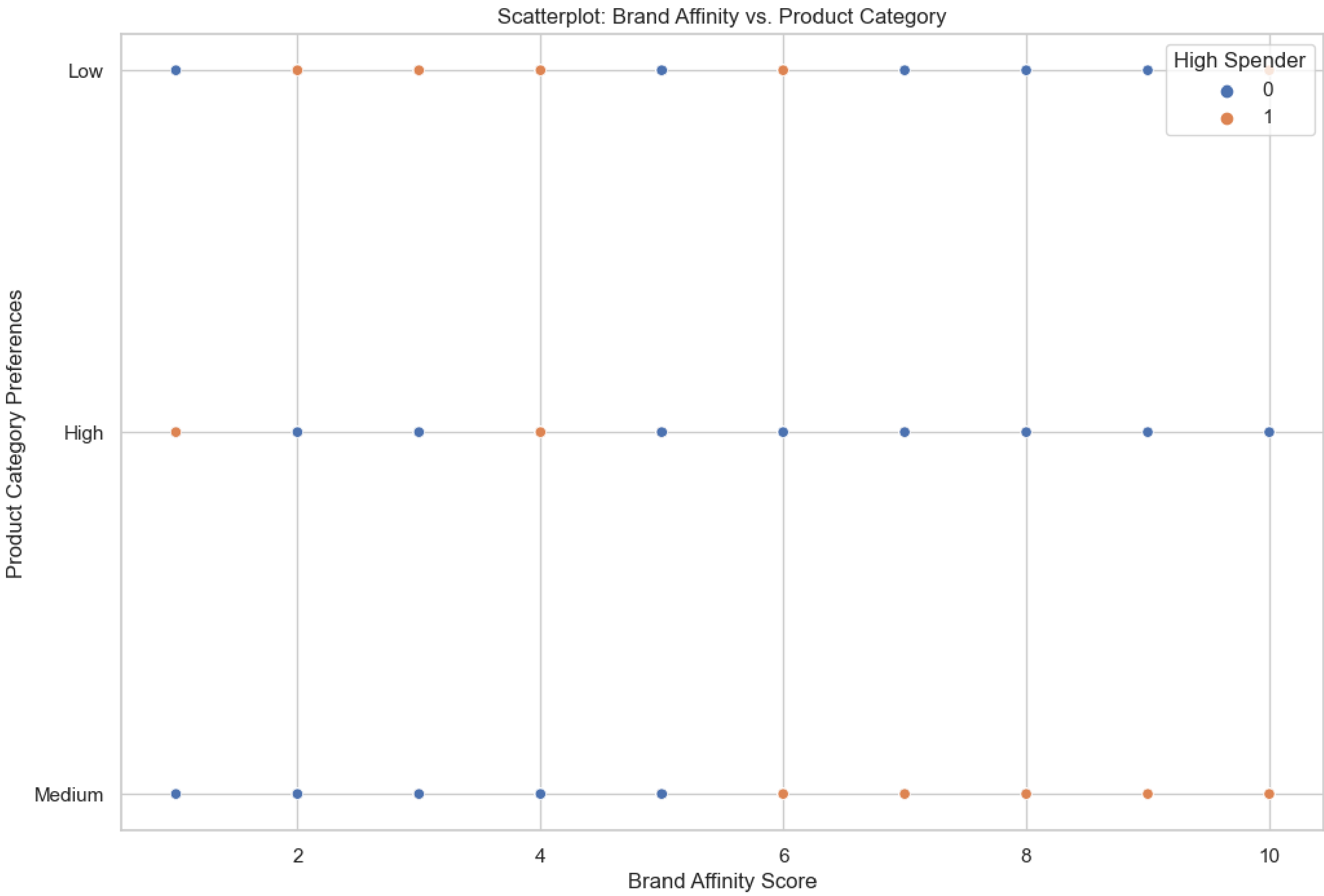
module 2 part 2

In [306]:

```
import seaborn as sns
import matplotlib.pyplot as plt


sns.set(style="whitegrid", palette="pastel")

plt.figure(figsize=(12, 6))
sns.barplot(x='Income_Level', y='Purchase_Amount', data=df, palette='viridis')
plt.title('Total Purchase Amount by Income Level')
plt.xlabel('Income Level')
plt.ylabel('Total Purchase Amount')
plt.show()
```

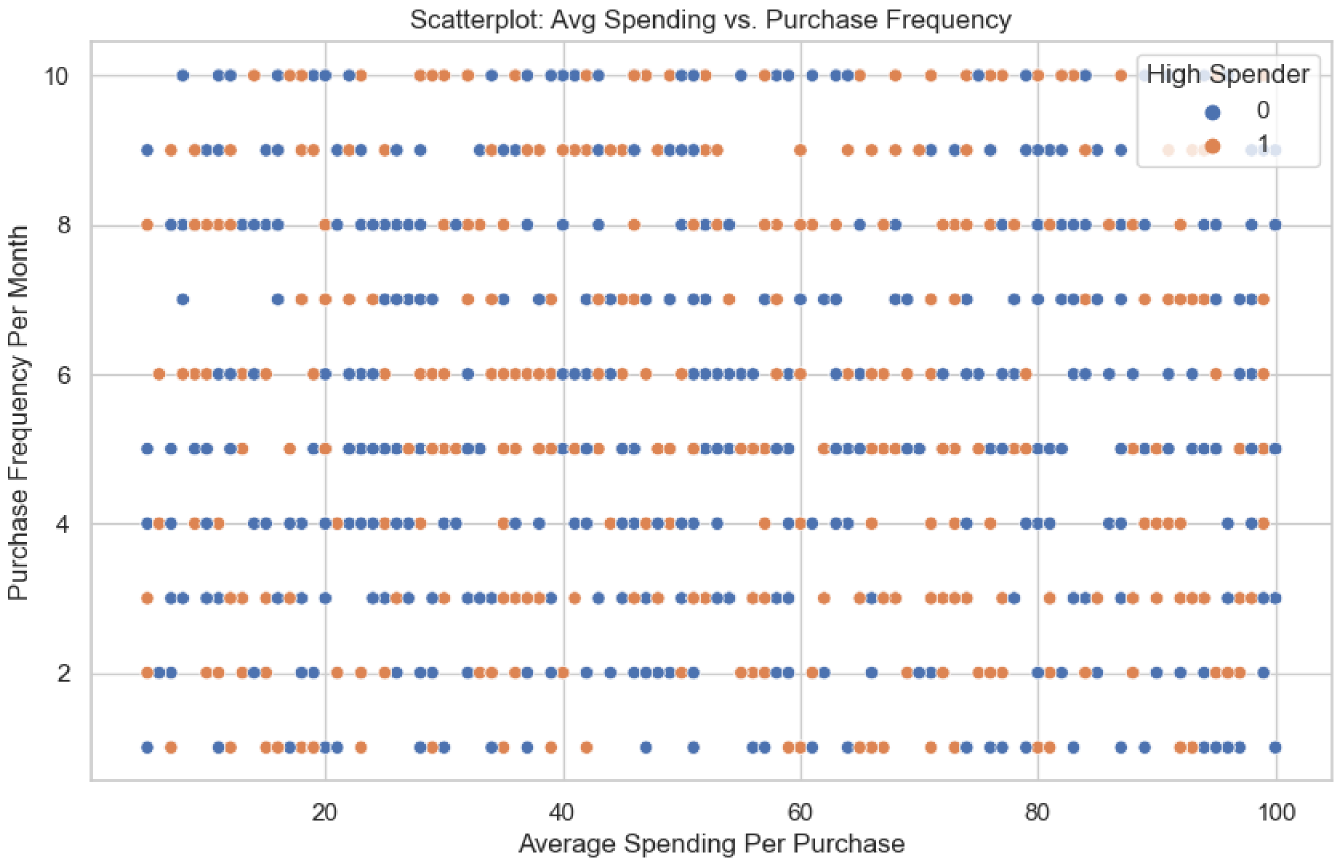


In [307]:
```
# 2. Scatterplot: Brand Affinity vs. Product Category
plt.figure(figsize=(12, 8))
sns.scatterplot(x='Brand_Affinity_Score', y='Product_Category_Preferences', data=df, hue='High_Spending_Customers', palette='deep')
plt.title('Scatterplot: Brand Affinity vs. Product Category')
plt.xlabel('Brand Affinity Score')
plt.ylabel('Product Category Preferences')
plt.legend(title='High Spender', loc='upper right')
plt.show()
```

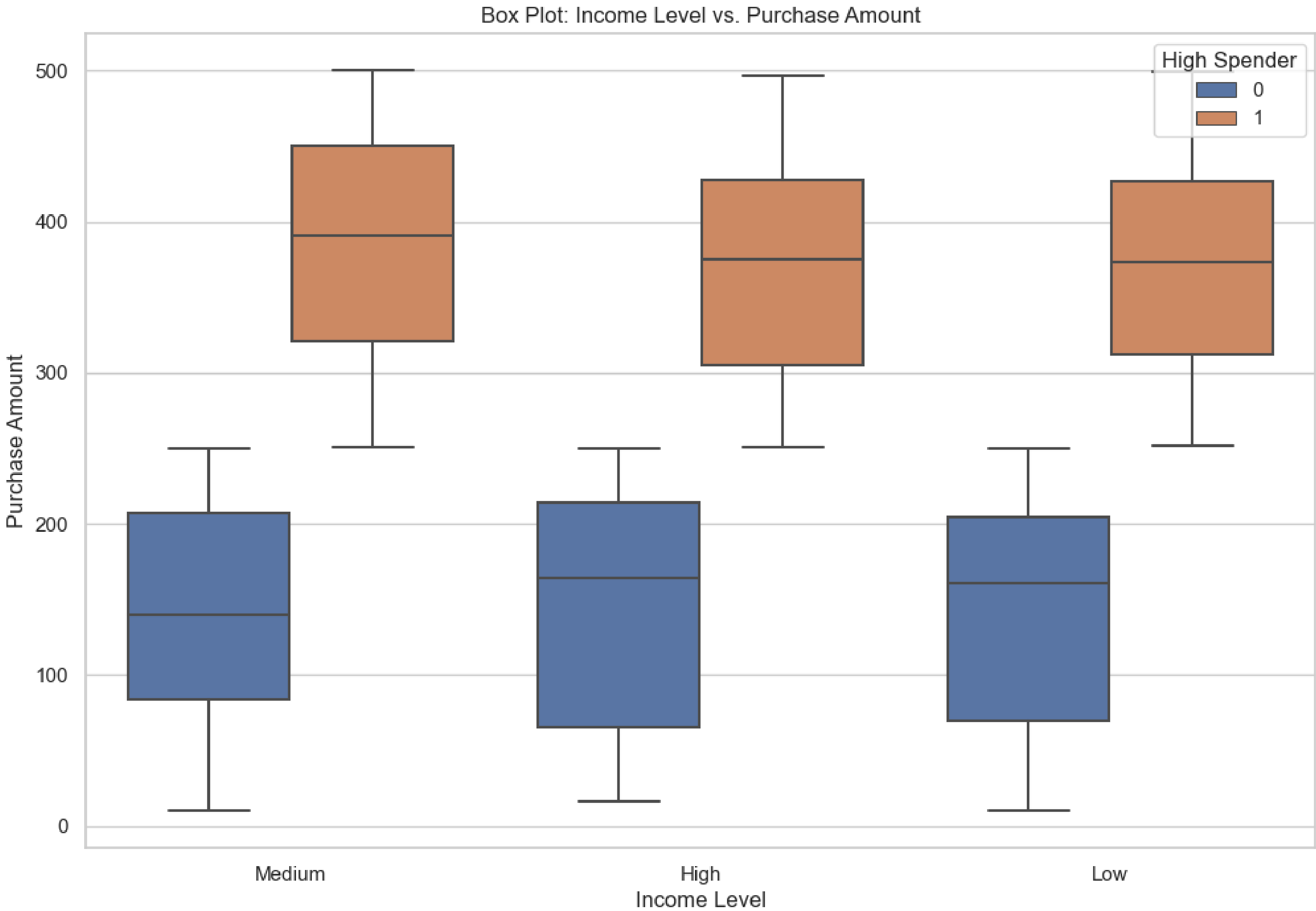


In [308]:
```
sns.set(style="whitegrid", palette="pastel")
```

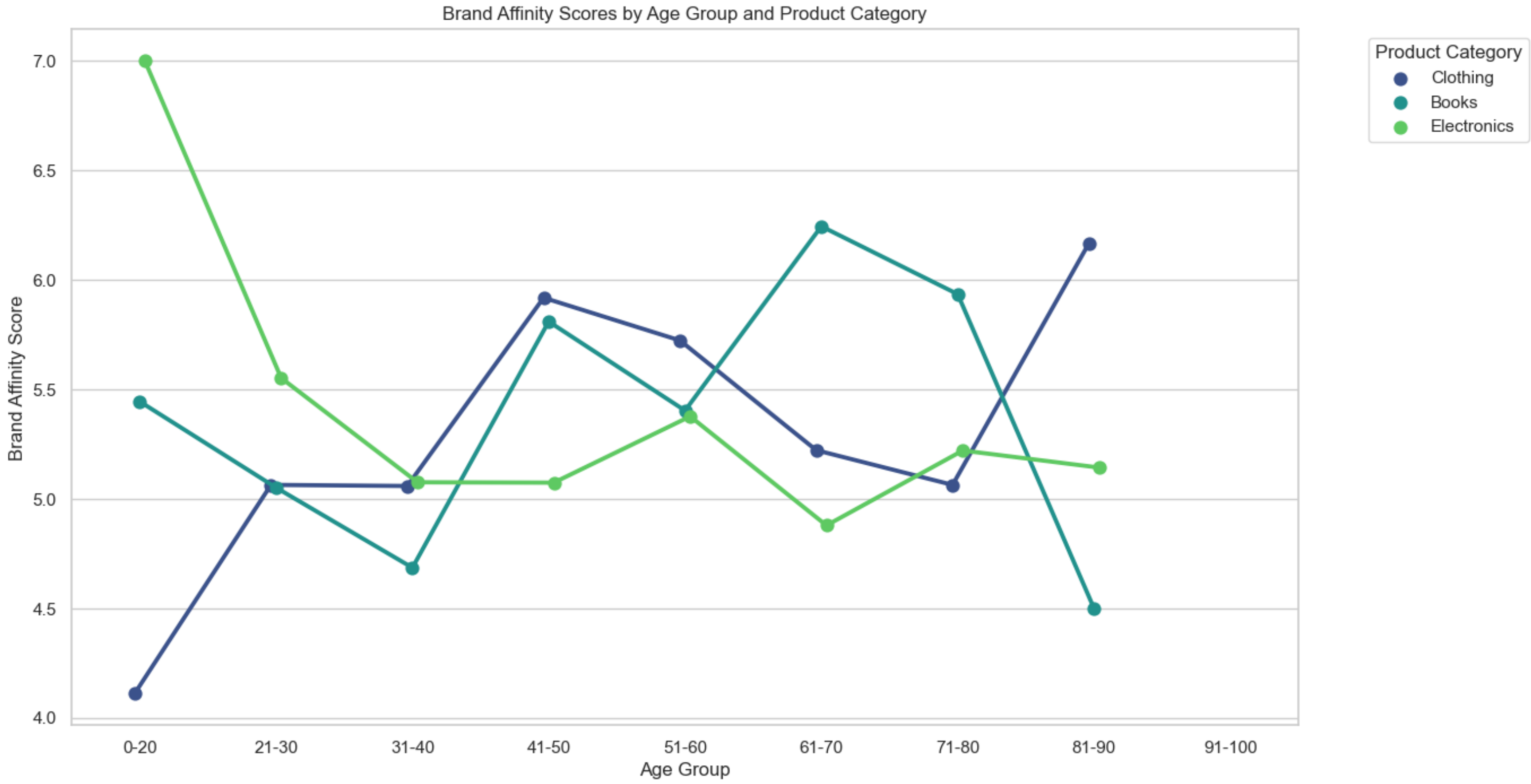
```
# Scatterplot: Average Spending Per Purchase vs. Purchase Frequency Per Month
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Average_Spending_Per_Purchase', y='Purchase_Frequency_Per_Month', data=df, hue='High_Spending_Customers', palette='dee
plt.title('Scatterplot: Avg Spending vs. Purchase Frequency')
plt.xlabel('Average Spending Per Purchase')
plt.ylabel('Purchase Frequency Per Month')
plt.legend(title='High Spender', loc='upper right')
plt.show()
```



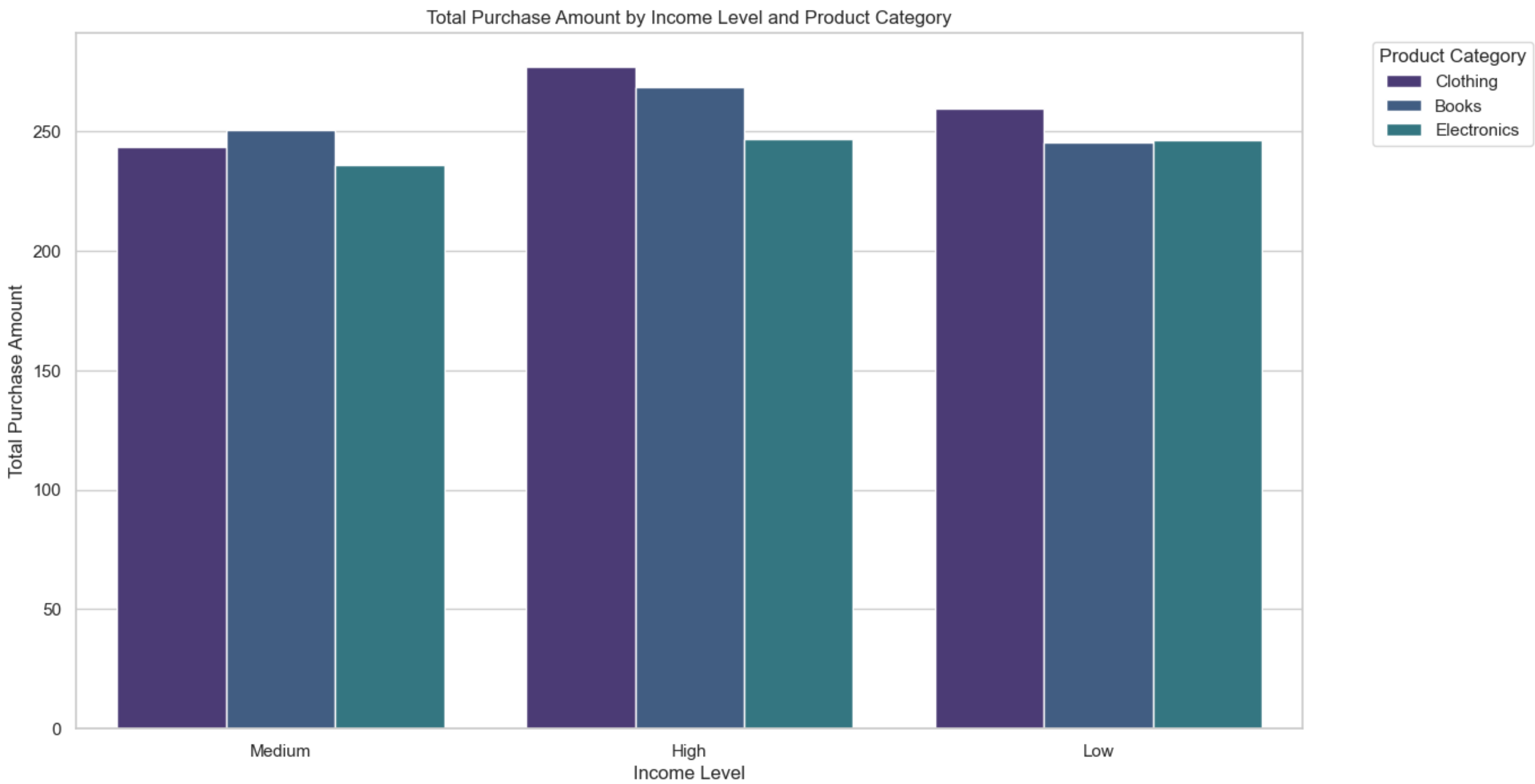
In [309]:
```
# Box Plot: Income Level vs. Purchase Amount
plt.figure(figsize=(12, 8))
sns.boxplot(x='Income_Level', y='Purchase_Amount', data=df, hue='High_Spending_Customers', palette='deep')
plt.title('Box Plot: Income Level vs. Purchase Amount')
plt.xlabel('Income Level')
plt.ylabel('Purchase Amount')
plt.legend(title='High Spender', loc='upper right')
plt.show()
```



In [310]:
```
import seaborn as sns
import matplotlib.pyplot as plt


sns.set(style="whitegrid", palette="viridis")


plt.figure(figsize=(14, 8))
sns.pointplot(x='Age_Group', y='Brand_Affinity_Score', hue='Product_Category', data=df, palette='viridis', dodge=True, errorbar=None)
plt.title('Brand Affinity Scores by Age Group and Product Category')
plt.xlabel('Age Group')
plt.ylabel('Brand Affinity Score')
plt.legend(title='Product Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

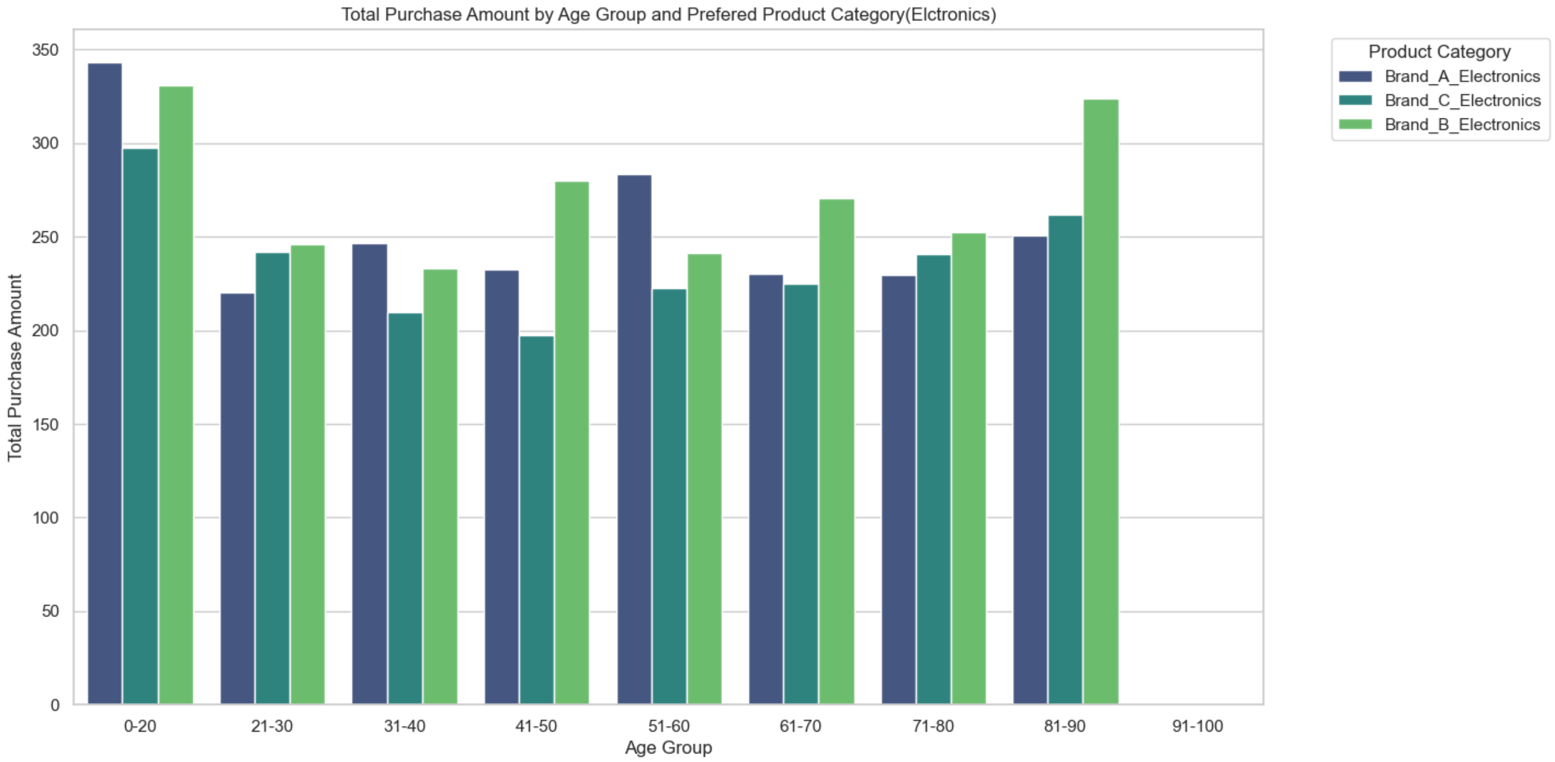


In [311]:
```
# Set the style and color palette
sns.set(style="whitegrid", palette="viridis")

plt.figure(figsize=(14, 8))
sns.barplot(x='Income_Level', y='Purchase_Amount', hue='Product_Category', data=df, errorbar=None)
plt.title('Total Purchase Amount by Income Level and Product Category')
plt.xlabel('Income Level')
plt.ylabel('Total Purchase Amount')
plt.legend(title='Product Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

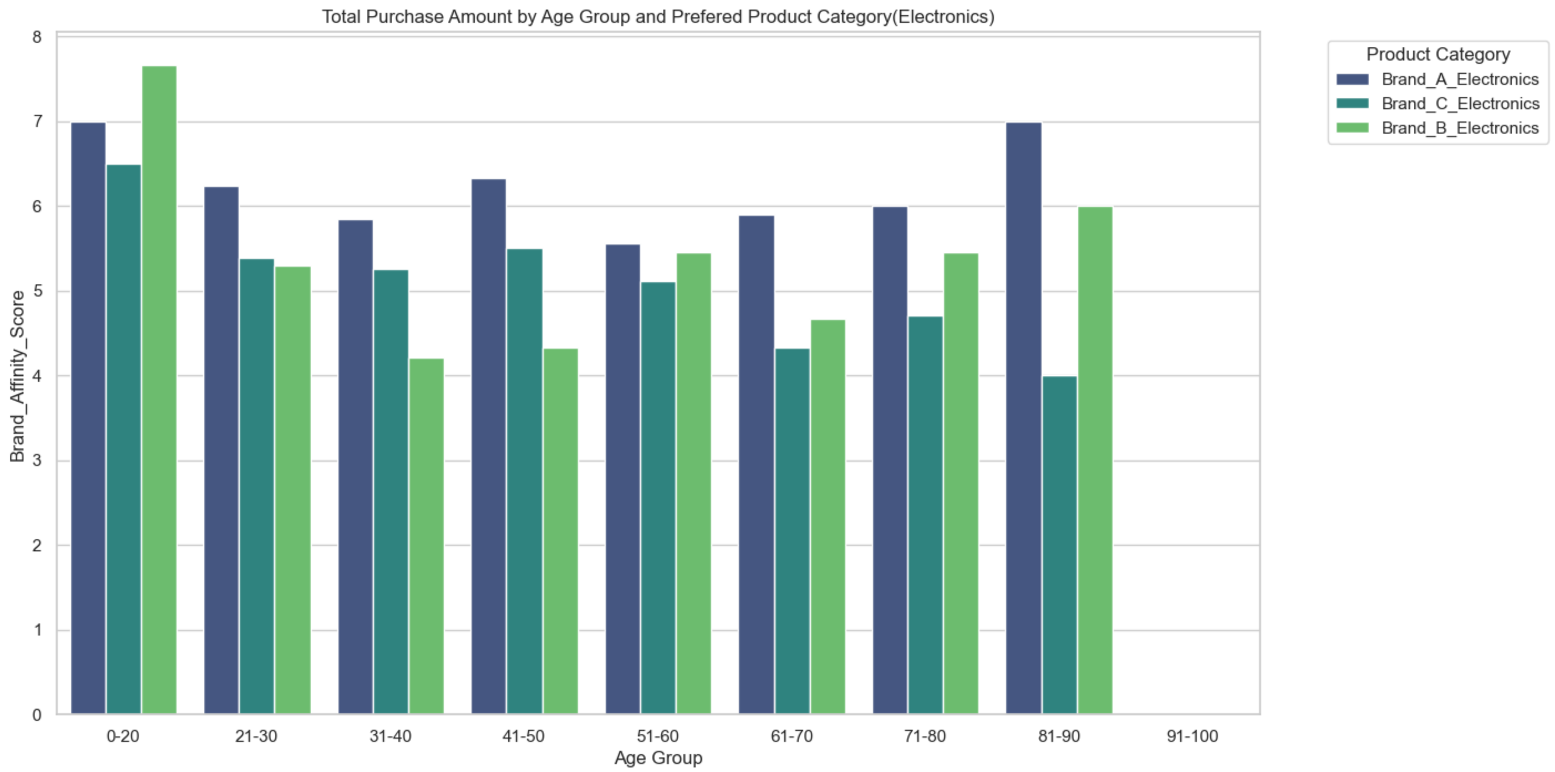


In [312]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style="whitegrid", palette="viridis")

selected_categories = ['Brand_A_Electronics', 'Brand_B_Electronics', 'Brand_C_Electronics']
filtered_df = df[df['Preferred_Brand_Category'].isin(selected_categories)]

plt.figure(figsize=(14, 8))
sns.barplot(x='Age_Group', y='Purchase_Amount',data=filtered_df, hue='Preferred_Brand_Category', palette='viridis', errorbar=None)
plt.title('Total Purchase Amount by Age Group and Prefered Product Category(Elctronics)')
```

```
plt.xlabel('Age Group')
plt.ylabel('Total Purchase Amount')
plt.legend(title='Product Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

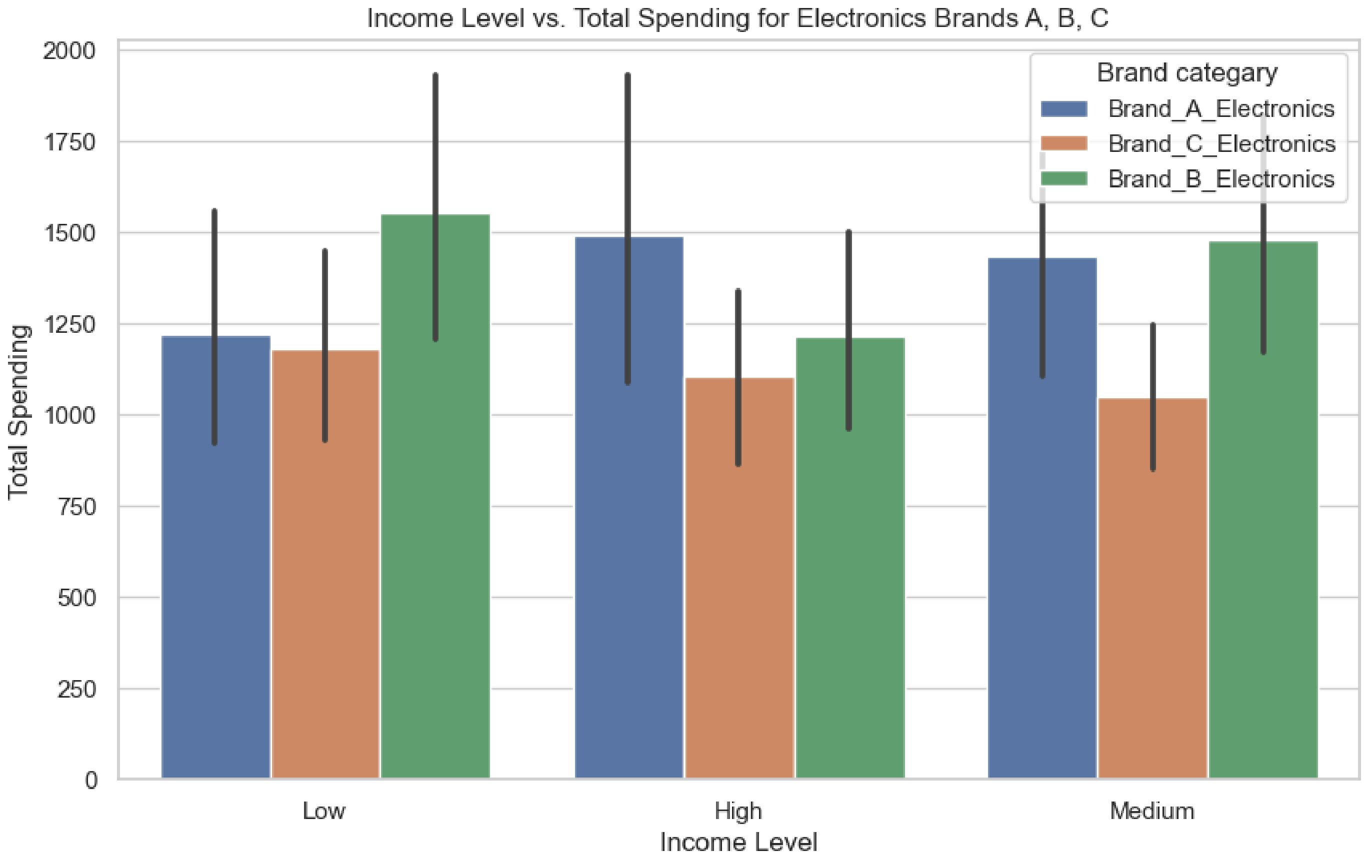


In [313]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style="whitegrid", palette="viridis")

selected_categories = ['Brand_A_Electronics', 'Brand_B_Electronics', 'Brand_C_Electronics']
filtered_df = df[df['Preferred_Brand_Category'].isin(selected_categories)]

plt.figure(figsize=(14, 8))
sns.barplot(x='Age_Group', y='Brand_Affinity_Score', data=filtered_df, hue='Preferred_Brand_Category', palette='viridis', errorbar=None)
plt.title('Total Purchase Amount by Age Group and Prefered Product Category(Electronics)')
plt.xlabel('Age Group')
plt.ylabel('Brand_Affinity_Score')
plt.legend(title='Product Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

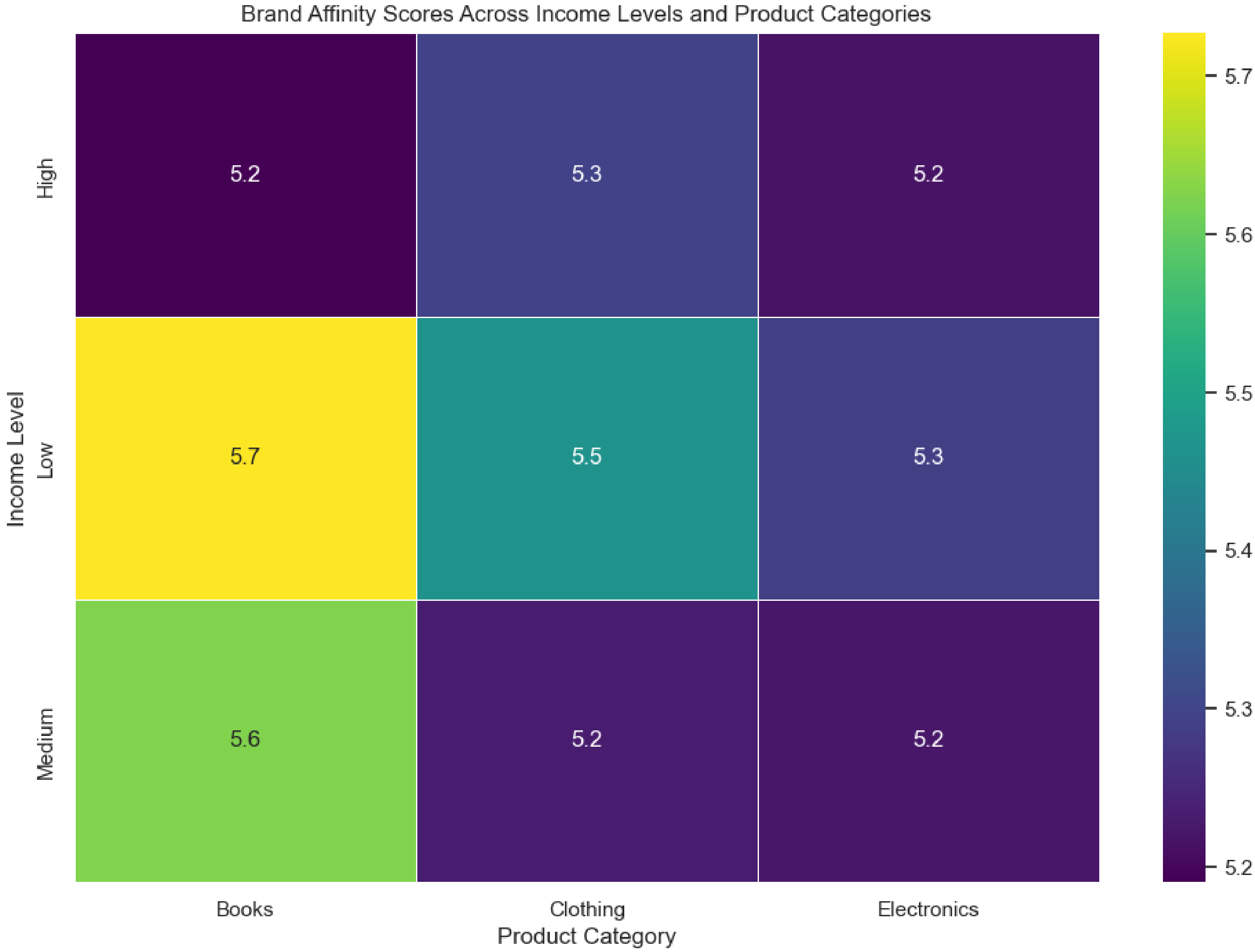


In [314]:
```
# Bar Plot: Income Level vs. Total Spending
import seaborn as sns
import matplotlib.pyplot as plt
```

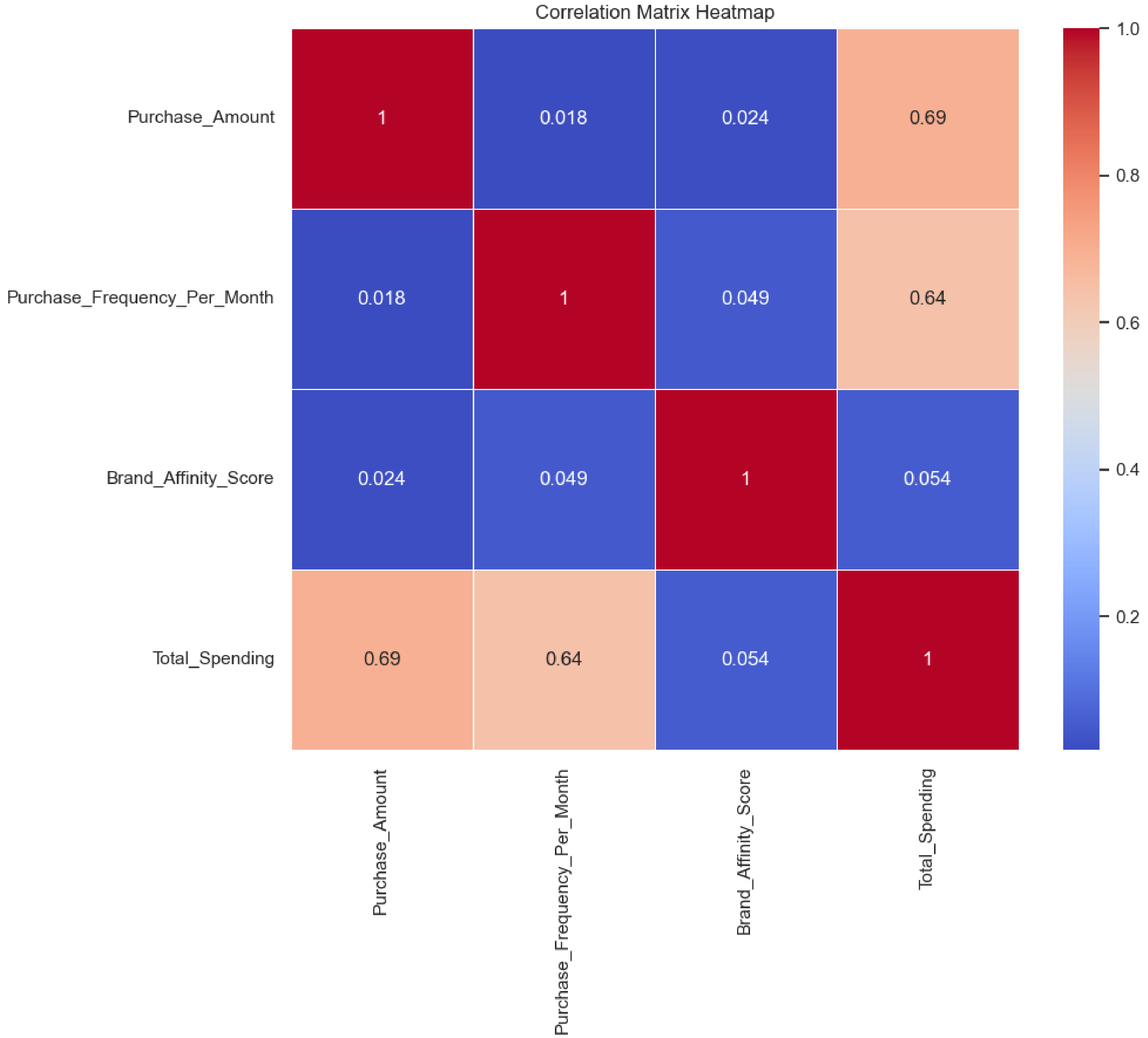
```
selected_categories = ['Brand_A_Electronics', 'Brand_B_Electronics', 'Brand_C_Electronics']
filtered_df = df[df['Preferred_Brand_Category'].isin(selected_categories)]


plt.figure(figsize=(10, 6))
sns.barplot(x='Income_Level', y='Total_Spending', data=filtered_df, hue='Preferred_Brand_Category', palette='deep')
plt.title('Income Level vs. Total Spending for Electronics Brands A, B, C')
plt.xlabel('Income Level')
plt.ylabel('Total Spending')
plt.legend(title='Brand categary', loc='upper right')
plt.show()
```



In [315]:
```
import seaborn as sns
import matplotlib.pyplot as plt


heatmap_data = df.pivot_table(index='Income_Level', columns='Product_Category', values='Brand_Affinity_Score', aggfunc='mean')


sns.set(style="whitegrid", palette="viridis")

# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(heatmap_data, annot=True, cmap='viridis', fmt=".1f", linewidths=.5)
plt.title('Brand Affinity Scores Across Income Levels and Product Categories')
plt.xlabel('Product Category')
plt.ylabel('Income Level')
plt.show()
```

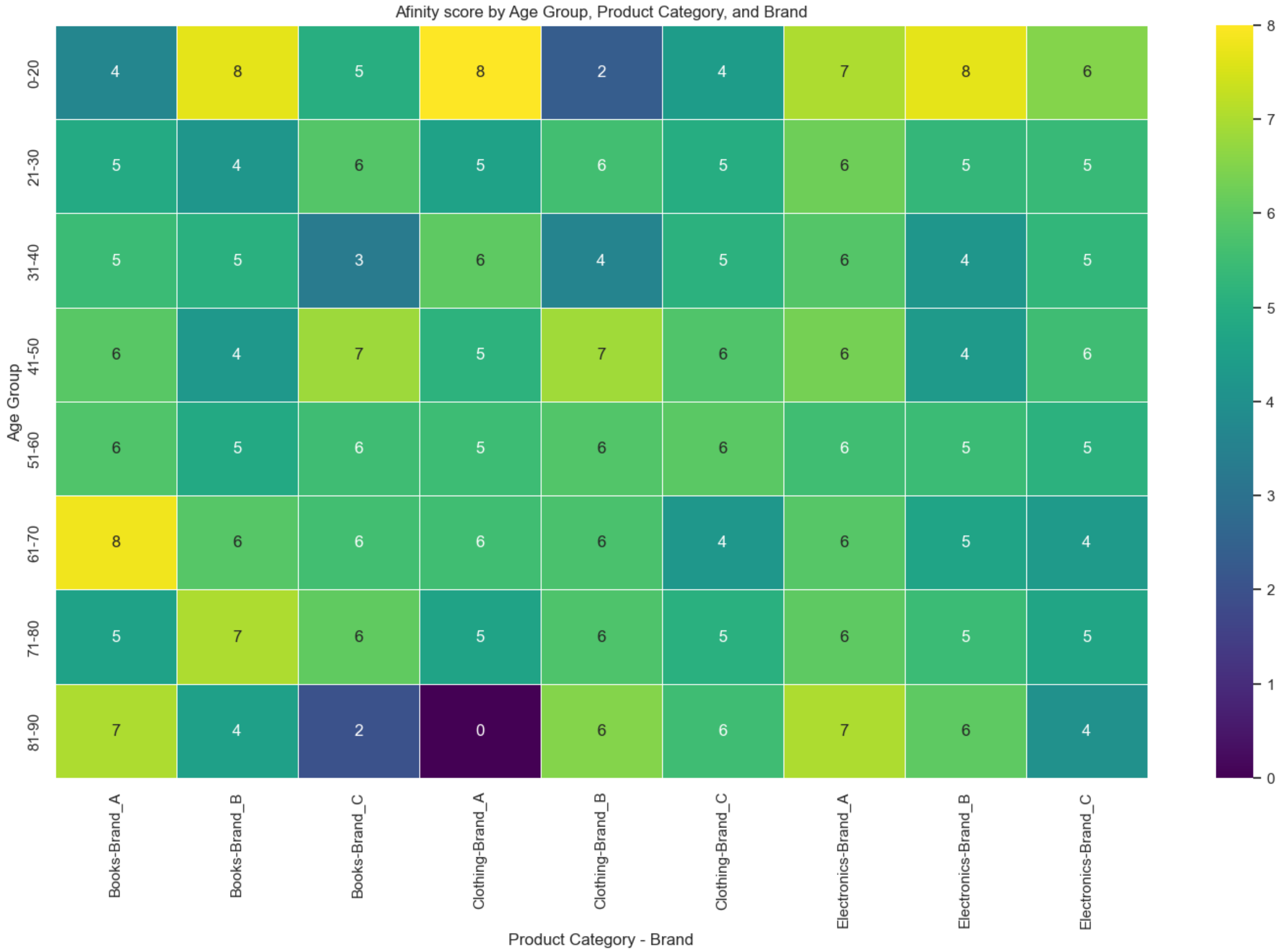


In [316]:
```
# Heatmap: Correlation Matrix
correlation_matrix = df[['Purchase_Amount', 'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score', 'Total_Spending']].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```

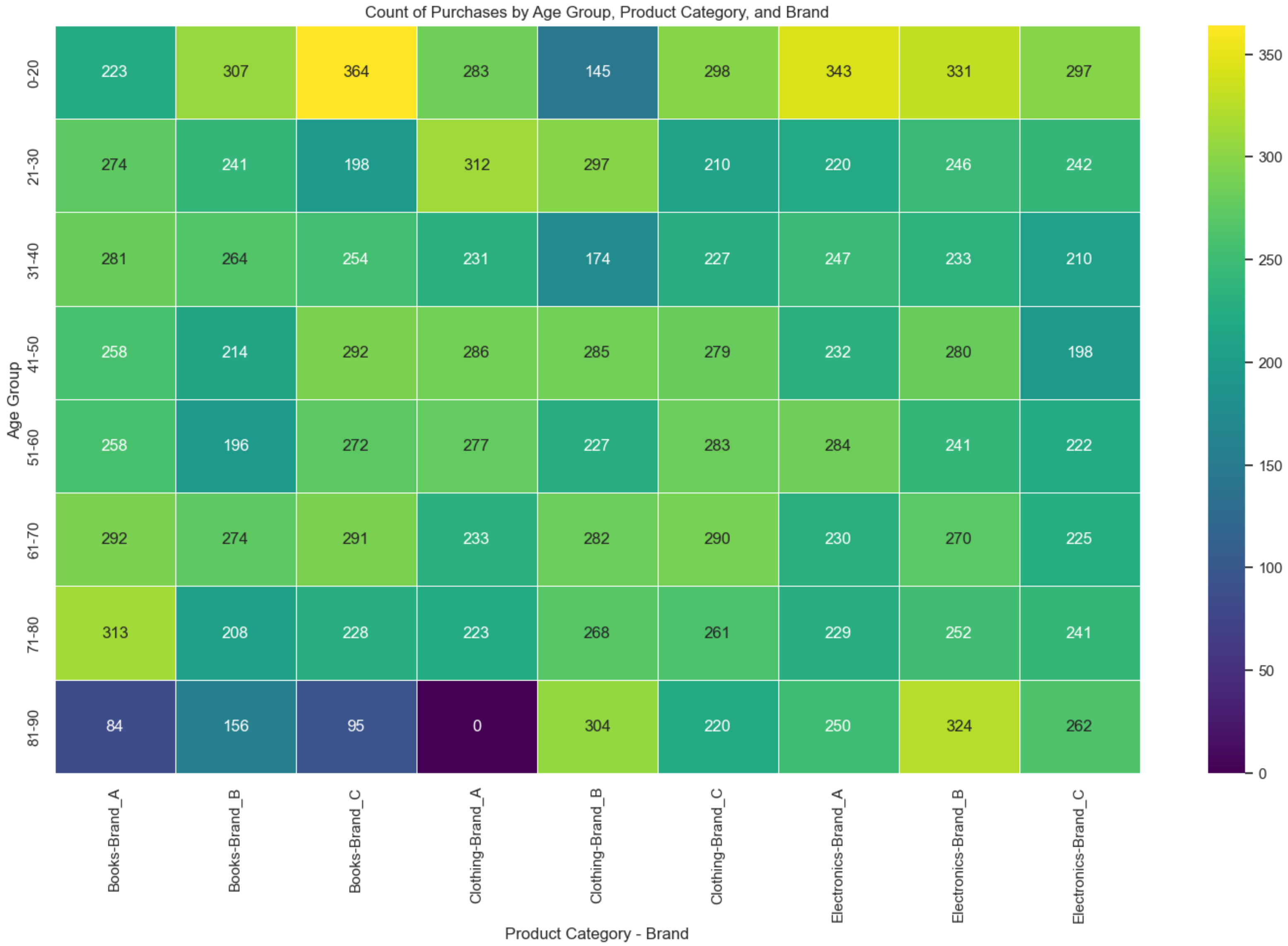


In [317]:

```
heatmap_data = df.pivot_table(index='Age_Group', columns=['Product_Category', 'Brand'], values='Brand_Affinity_Score', fill_value=0)

sns.set(style="whitegrid", palette="viridis")

# Create a heatmap
plt.figure(figsize=(18, 10))
sns.heatmap(heatmap_data, annot=True, cmap='viridis', fmt=".0f", linewidths=.5)
plt.title('Afinity score by Age Group, Product Category, and Brand')
plt.xlabel('Product Category - Brand')
plt.ylabel('Age Group')
plt.show()
```

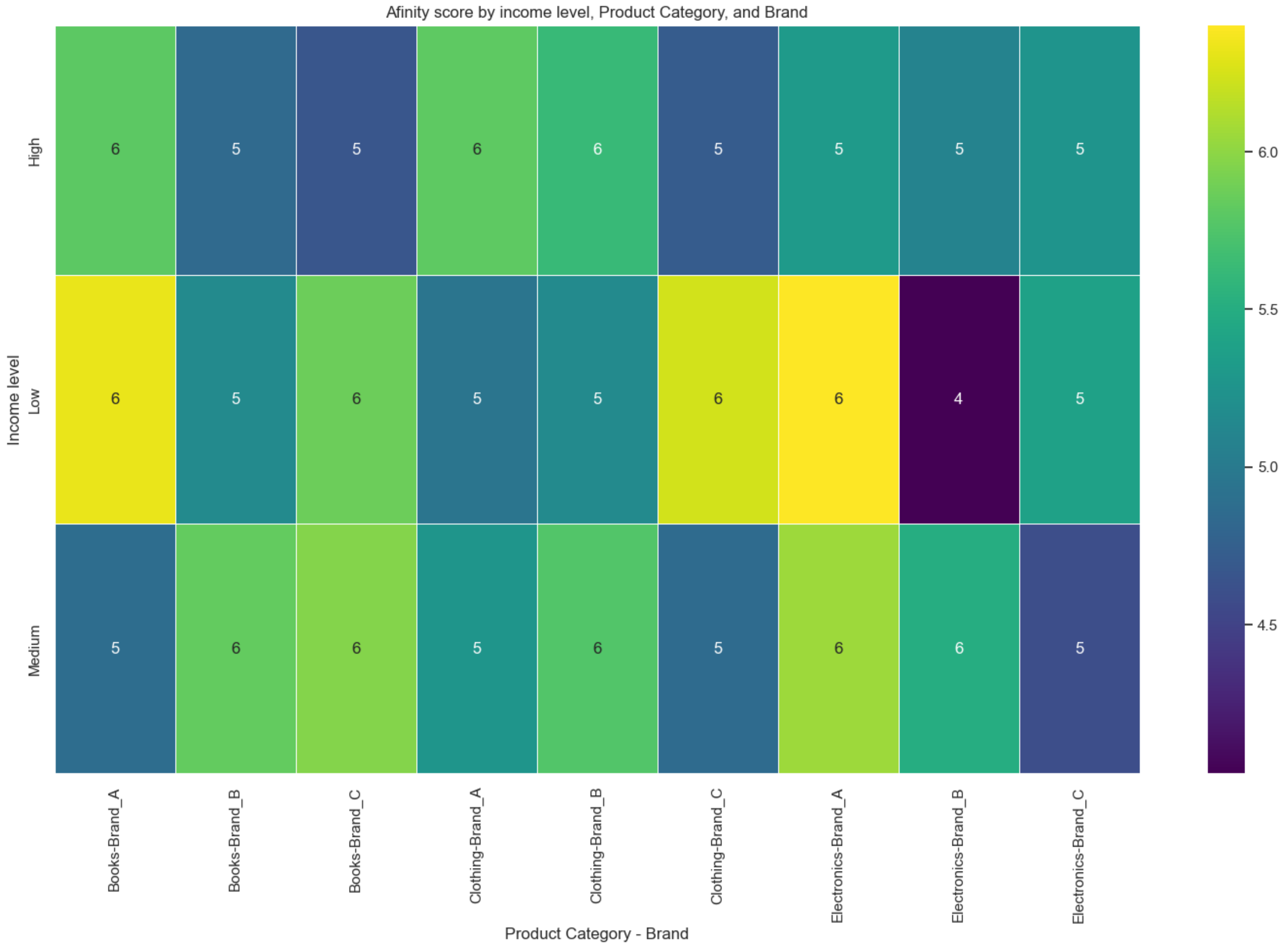


In [318]:
```
heatmap_data = df.pivot_table(index='Age_Group', columns=['Product_Category', 'Brand'], values='Purchase_Amount', fill_value=0)


sns.set(style="whitegrid", palette="viridis")

# Create a heatmap
plt.figure(figsize=(18, 10))
sns.heatmap(heatmap_data, annot=True, cmap='viridis', fmt=".0f", linewidths=.5)
plt.title('Count of Purchases by Age Group, Product Category, and Brand')
plt.xlabel('Product Category - Brand')
plt.ylabel('Age Group')
plt.show()
```



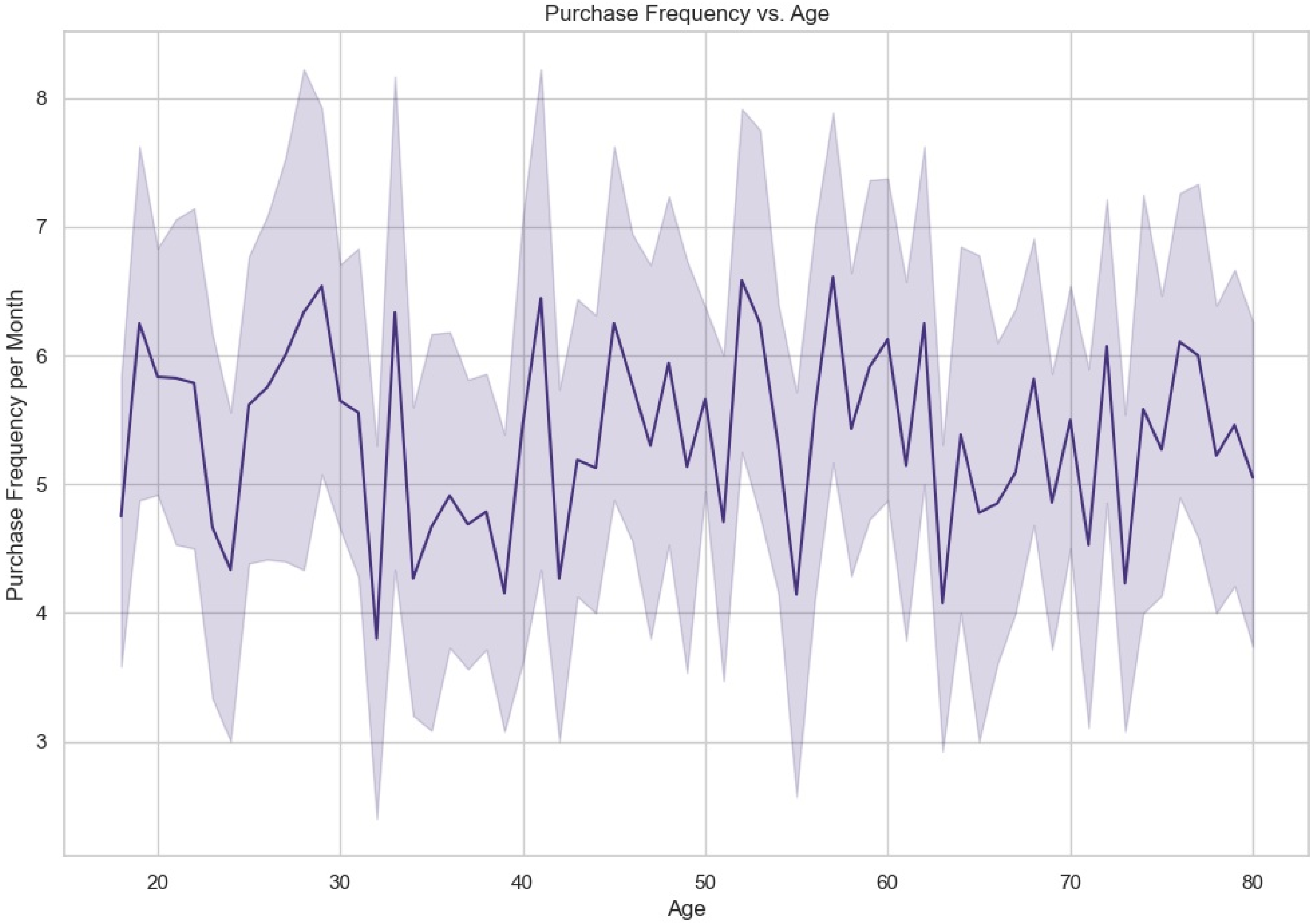
In [319]:

```
heatmap_data = df.pivot_table(index='Income_Level', columns=['Product_Category', 'Brand'], values='Brand_Affinity_Score', fill_value=0)


sns.set(style="whitegrid", palette="viridis")

# Create a heatmap
plt.figure(figsize=(18, 10))
sns.heatmap(heatmap_data, annot=True, cmap='viridis', fmt=".0f", linewidths=.5)
plt.title('Afinity score by income level, Product Category, and Brand')
plt.xlabel('Product Category - Brand')
plt.ylabel('Income level')
plt.show()
```



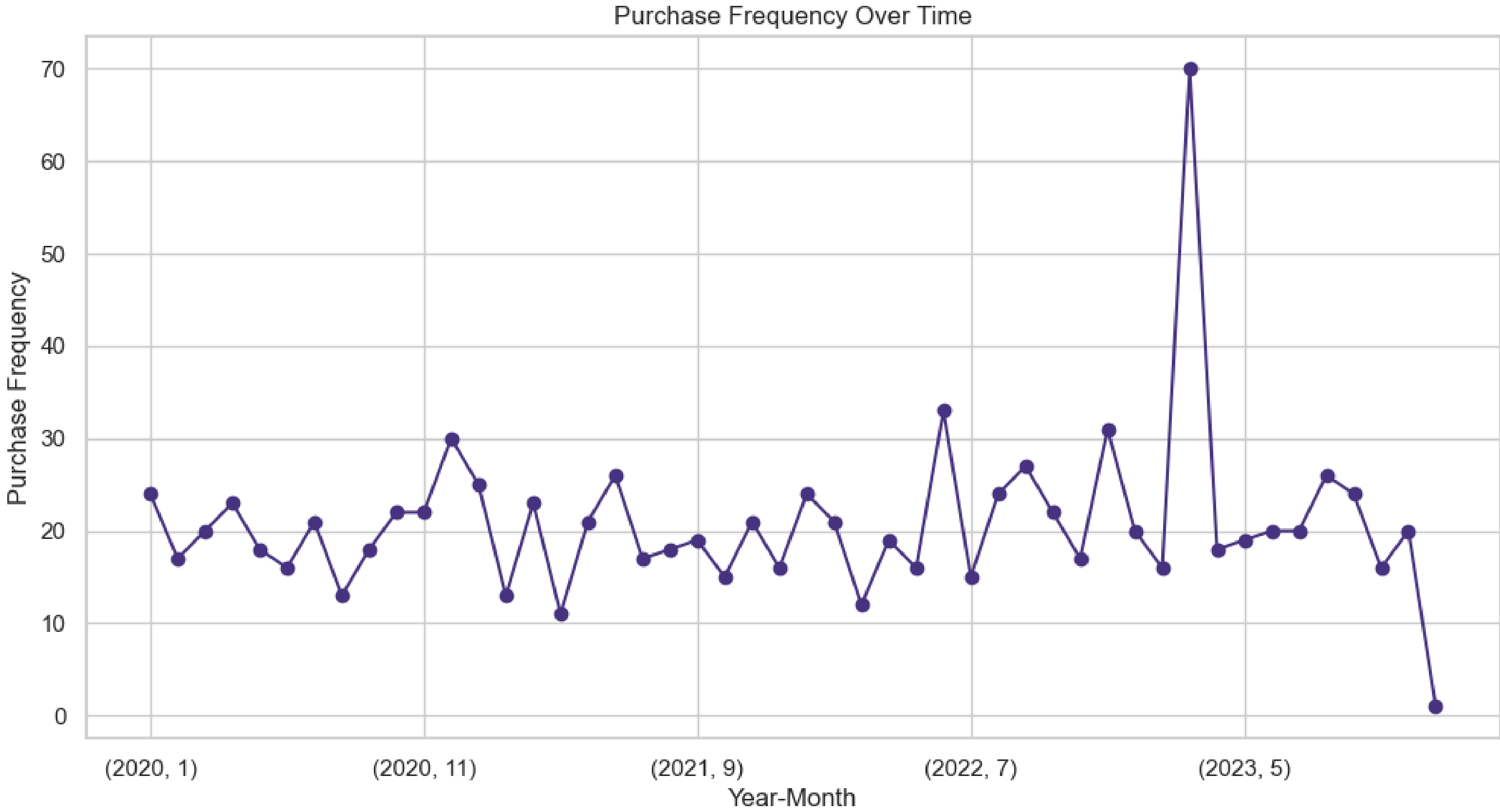
Part 3

In [320]:
```
plt.figure(figsize=(12, 8))
sns.lineplot(x='Age', y='Purchase_Frequency_Per_Month', data=df)
plt.title('Purchase Frequency vs. Age')
plt.xlabel('Age')
plt.ylabel('Purchase Frequency per Month')
plt.show()
```

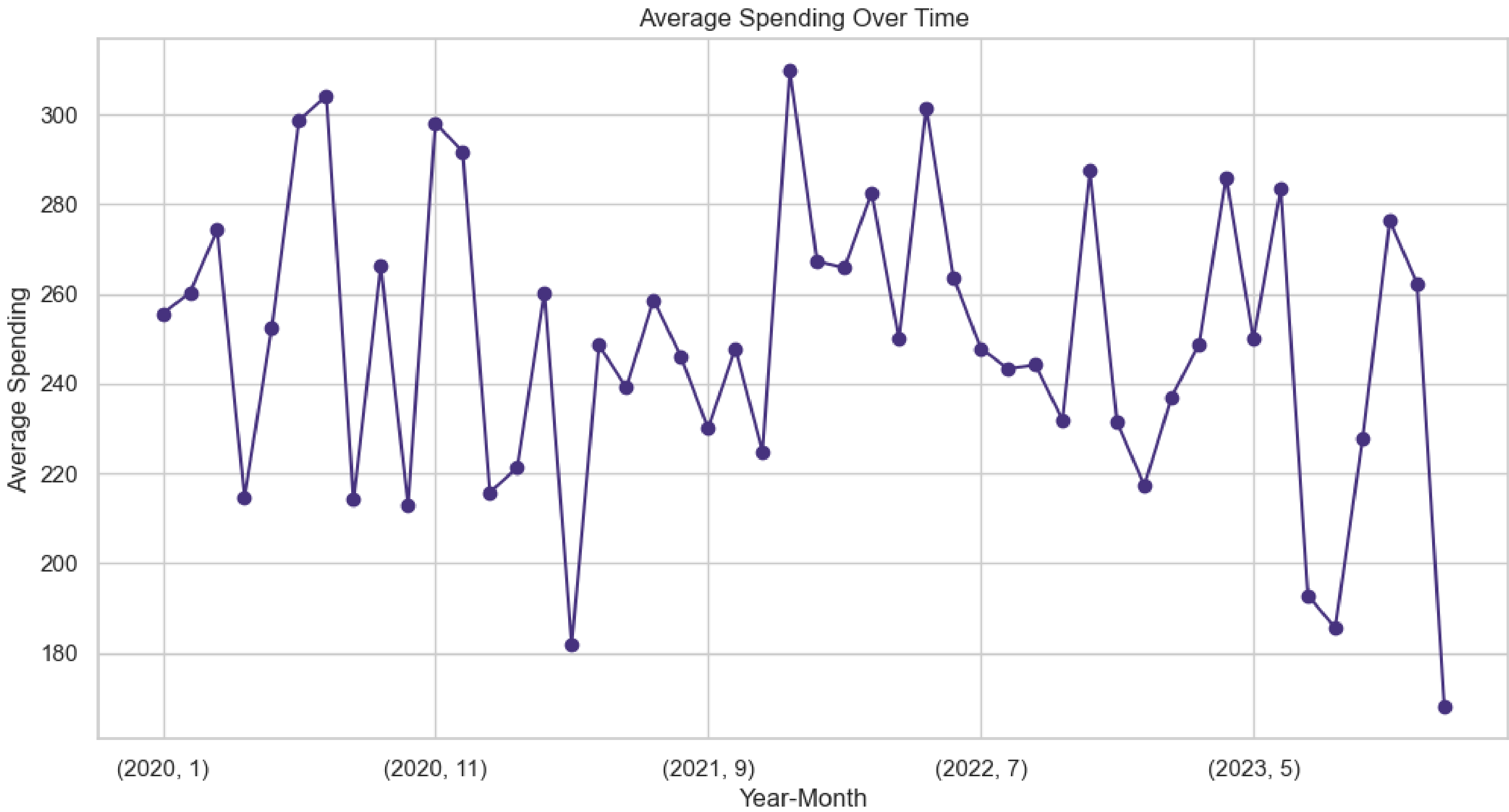


In [321]:
```
df['Purchase_Date'] = pd.to_datetime(df['Purchase_Date'])
df['Month'] = df['Purchase_Date'].dt.month
df['Year'] = df['Purchase_Date'].dt.year
```

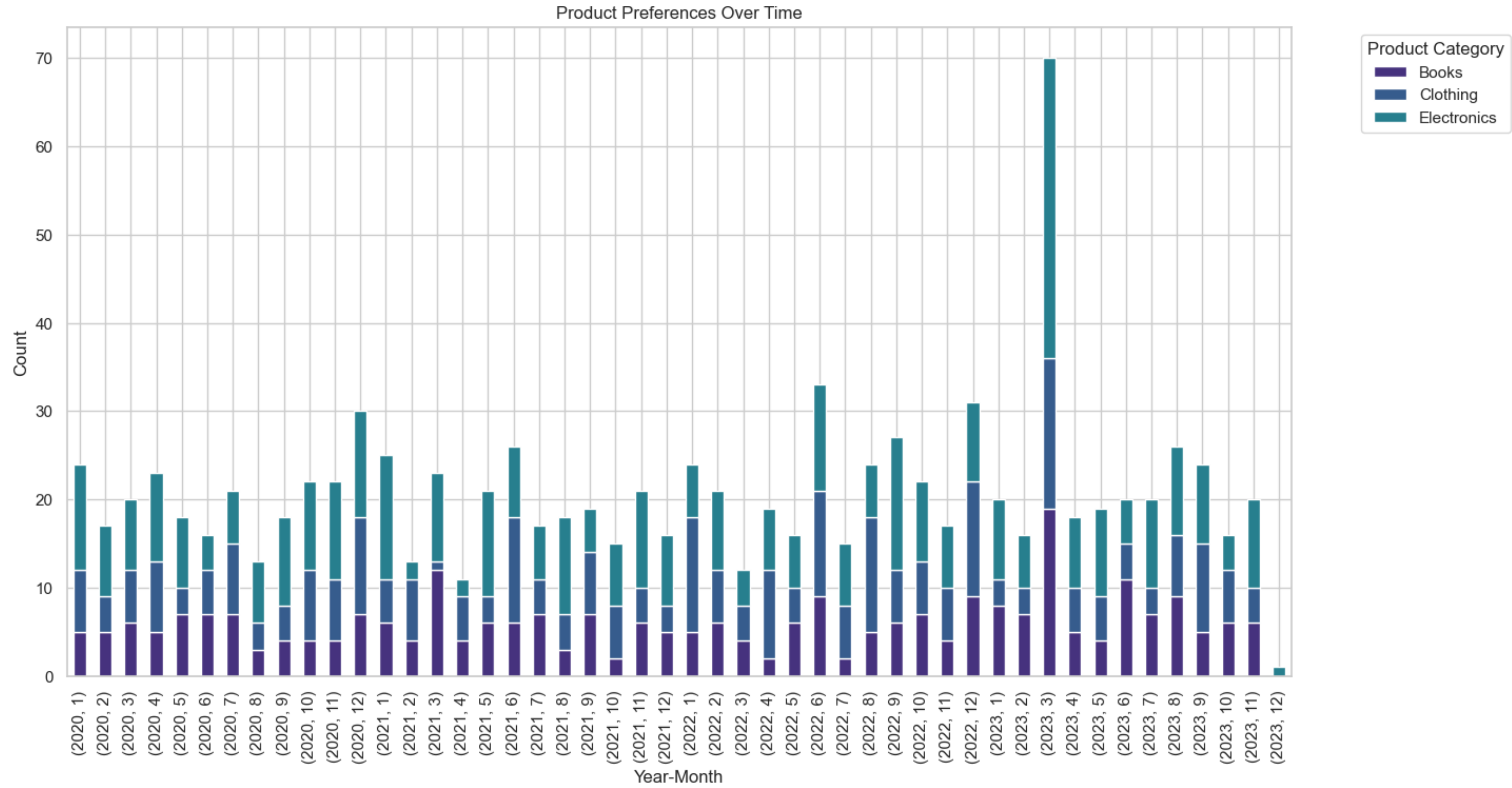
In [322]:
```
purchase_frequency = df.groupby(['Year', 'Month']).size()

plt.figure(figsize=(12, 6))
purchase_frequency.plot(marker='o')
plt.title('Purchase Frequency Over Time')
plt.xlabel('Year-Month')
plt.ylabel('Purchase Frequency')
plt.show()
```



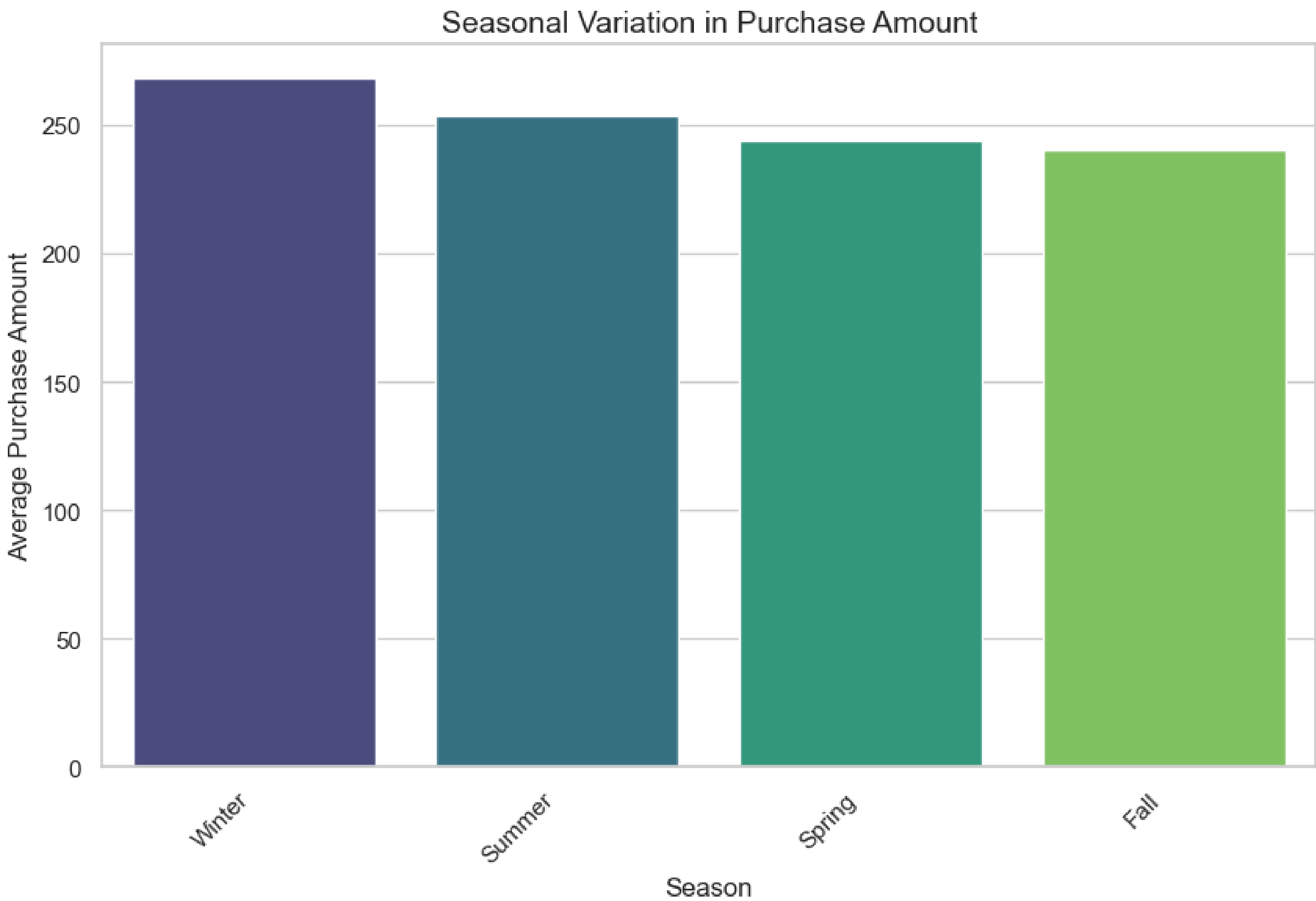
In [323]:
```
average_spending = df.groupby(['Year', 'Month'])['Purchase_Amount'].mean()

plt.figure(figsize=(12, 6))
average_spending.plot(marker='o')
plt.title('Average Spending Over Time')
plt.xlabel('Year-Month')
plt.ylabel('Average Spending')
plt.show()
```



In [324]:
```
product_preferences = df.groupby(['Year', 'Month', 'Product_Category']).size().unstack()

product_preferences.plot(kind='bar', stacked=True, figsize=(15, 8))
plt.title('Product Preferences Over Time')
plt.xlabel('Year-Month')
plt.ylabel('Count')
plt.legend(title='Product Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



In [325]:
```
import seaborn as sns
import matplotlib.pyplot as plt


seasonal_variation = df.groupby('Season')['Purchase_Amount'].mean().sort_values(ascending=False)

plt.figure(figsize=(10, 6))
ax = sns.barplot(x=seasonal_variation.index, y=seasonal_variation.values, palette='viridis')

plt.title('Seasonal Variation in Purchase Amount', fontsize=14)
plt.xlabel('Season', fontsize=12)
plt.ylabel('Average Purchase Amount', fontsize=12)

ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

# Show the plot
plt.show()
```



In [326]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 22 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Customer_ID                    1000 non-null   object
 1   Age                            1000 non-null   int32
 2   Gender                         1000 non-null   object
 3   Income_Level                   1000 non-null   object
 4   Address                        1000 non-null   object
 5   Transaction_ID                 1000 non-null   object
 6   Purchase_Date                  1000 non-null   datetime64[ns]
 7   Product_ID                     1000 non-null   object
 8   Product_Category               1000 non-null   object
 9   Brand                          1000 non-null   object
 10  Purchase_Amount                1000 non-null   int32
 11  Average_Spending_Per_Purchase  1000 non-null   int32
 12  Purchase_Frequency_Per_Month   1000 non-null   int32
 13  Brand_Affinity_Score           1000 non-null   int32
 14  Product_Category_Preferences   1000 non-null   object
 15  Month                          1000 non-null   int64
 16  Year                           1000 non-null   int64
 17  Season                         1000 non-null   object
 18  Total_Spending                 1000 non-null   int32
 19  Preferred_Brand_Category       1000 non-null   object
 20  High_Spending_Customers        1000 non-null   int32
 21  Age_Group                      1000 non-null   category
dtypes: category(1), datetime64[ns](1), int32(7), int64(2), object(11)
memory usage: 138.2+ KB
```

In [327]:
```
#i am starting module 3 from here (clustring analysis)
```

In [ ]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import DBSCAN

#Standardize the features to ensure equal weightage in clustering.

scaled_features1 = ['Purchase_Amount', 'Average_Spending_Per_Purchase','Age',
                    'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score']
scaler = StandardScaler()
scaled_features = scaler.fit_transform(df[scaled_features1])
scaled_features
```

```
#Determine the number of clusters
#Elbow Method


wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='random', n_init=10, random_state=42)
    kmeans.fit(scaled_features)
    wcss.append(kmeans.inertia_)

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

In [ ]:
```
# Silhouette Analysis

for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, init='random', n_init=10, random_state=42)
    cluster_labels = kmeans.fit_predict(scaled_features)
    silhouette_avg = silhouette_score(scaled_features, cluster_labels)
    print(f"Silhouette Score for {i} clusters: {silhouette_avg}")
```

In [ ]:
```
from sklearn.metrics import silhouette_score

silhouette_scores = []
for i in range(2, 11):
    kmeans = KMeans(n_clusters=i,n_init=10, random_state=42)
    kmeans.fit(scaled_features)
    labels = kmeans.labels_
    silhouette_scores.append(silhouette_score(scaled_features, labels))

# Plotting the silhouette scores
plt.figure(figsize=(10, 5))
sns.lineplot(x=range(2, 11), y=silhouette_scores, marker='o')
plt.title('Silhouette Analysis')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.show()
```

In [ ]:
```
from sklearn.cluster import KMeans
import pandas as pd  # Assuming 'df' is your DataFrame

# Assuming 'features_for_clustering' contains the selected features for clustering
features_for_clustering = df[['Purchase_Amount', 'Age', 'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']]

# Define the number of clusters (k)
k = 6

# Apply K-Means algorithm
kmeans = KMeans(n_clusters=k, random_state=42)
df['Cluster_Labels'] = kmeans.fit_predict(features_for_clustering)

# Optional: If you want to see the resulting clusters in the DataFrame
df  # Add other columns as needed

# Visualize the clusters or perform further analysis as necessary
```

In [ ]:
```
# Assuming 'df' is your DataFrame with 'Cluster_Labels'
cluster_characteristics = df.groupby('Cluster_Labels').mean()

# Display the cluster characteristics
print(cluster_characteristics[['Purchase_Amount', 'Brand_Affinity_Score','Average_Spending_Per_Purchase']])
```

In [ ]:
```
pca = PCA(n_components=2)
reduced_data = pca.fit_transform(scaled_features)

# Plotting the clusters
plt.figure(figsize=(10, 6))
for i in range(k):
    plt.scatter(reduced_data[df['Cluster_Labels'] == i, 0], reduced_data[df['Cluster_Labels'] == i, 1], label=f'Cluster {i}')
plt.title('Clusters of Customers (Reduced to 2D using PCA)')
plt.xlabel('PCA Feature 1')
plt.ylabel('PCA Feature 2')
plt.legend()
plt.show()
```

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

# List of numeric columns to visualize
numeric_columns = df[['Purchase_Amount', 'Age', 'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']]
```

```
    # Loop through each numeric column
    for column in numeric_columns:
        # Visualize the numeric column across clusters
        sns.barplot(x='Cluster_Labels', y=column, data=df)
        plt.title(f'Average {column} Across Clusters')
        plt.show()
```

module 3 part 3

In [ ]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns

# Select features for clustering
features_for_clustering = df[['Purchase_Amount', 'Age', 'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']]

# Standardize the features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features_for_clustering)

# Define the number of clusters (k)
k = 6

# Apply K-Means++ algorithm
kmeans_plusplus = KMeans(n_clusters=k, init='k-means++', random_state=42)
df['Cluster_Labels++'] = kmeans_plusplus.fit_predict(scaled_features)

# Assuming 'df' is your DataFrame with 'Cluster_Labels'
cluster_characteristics = df.groupby('Cluster_Labels++').mean()

# Display the cluster characteristics
print(cluster_characteristics[['Purchase_Amount', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']])

# Apply PCA for dimensionality reduction
pca = PCA(n_components=2)
reduced_data = pca.fit_transform(scaled_features)

# Plotting the clusters
plt.figure(figsize=(10, 6))
for i in range(k):
    plt.scatter(reduced_data[df['Cluster_Labels++'] == i, 0], reduced_data[df['Cluster_Labels++'] == i, 1], label=f'Cluster {i}')
plt.title('Clusters of Customers (Reduced to 2D using PCA)')
plt.xlabel('PCA Feature 1')
plt.ylabel('PCA Feature 2')
plt.legend()
plt.show()
```

In [ ]:
```
# Assuming 'df' is your DataFrame with both sets of cluster labels
# Group by each set of cluster labels and compute cluster characteristics
cluster_characteristics_kmeans = df.groupby('Cluster_Labels').mean()
cluster_characteristics_kmeans_plusplus = df.groupby('Cluster_Labels++').mean()

# Display and compare the cluster characteristics
print("Cluster Characteristics for Regular K-Means:")
print(cluster_characteristics_kmeans[['Purchase_Amount', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']])

print("\nCluster Characteristics for K-Means++:")
print(cluster_characteristics_kmeans_plusplus[['Purchase_Amount', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']])
```

In [ ]:
```
import time

# Measure time for Regular K-Means
start_time_kmeans = time.time()
kmeans.fit(features_for_clustering)
end_time_kmeans = time.time()
time_taken_kmeans = end_time_kmeans - start_time_kmeans

# Measure time for K-Means++
start_time_kmeans_plusplus = time.time()
kmeans_plusplus.fit(features_for_clustering)
end_time_kmeans_plusplus = time.time()
time_taken_kmeans_plusplus = end_time_kmeans_plusplus - start_time_kmeans_plusplus

print("Time taken for Regular K-Means:", time_taken_kmeans)
print("Time taken for K-Means++:", time_taken_kmeans_plusplus)
```

In [ ]:
```
silhouette_regular = silhouette_score(scaled_features, df['Cluster_Labels'])
# Silhouette Score for K-Means++
silhouette_plus = silhouette_score(scaled_features, df['Cluster_Labels++'])
```

```
iterations_regular = kmeans_regular.n_iter_
# Number of iterations for K-Means++
iterations_plus = kmeans_plus.n_iter_

print(f"Number of iterations for Regular K-Means: {iterations_regular}")
print(f"Number of iterations for K-Means++: {iterations_plus}")

print(f"Silhouette Score for Regular K-Means: {silhouette_regular}")
print(f"Silhouette Score for K-Means++: {silhouette_plus}")
```

In [ ]:
```
df
```

In [ ]:
```
from sklearn.cluster import DBSCAN
from sklearn.metrics import silhouette_score
import numpy as np

# Select features for clustering
features_for_clustering = df[['Purchase_Amount', 'Age', 'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']]

# Standardize the features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features_for_clustering)

# Experiment with different values of eps and MinPts
eps_values = np.arange(0.1, 2.0, 0.1)
min_samples_values = range(2, 10)

best_silhouette_score = -1
best_eps = None
best_min_samples = None

# Iterate over different parameter combinations
for eps in eps_values:
    for min_samples in min_samples_values:
        # Apply DBSCAN
        dbscan = DBSCAN(eps=eps, min_samples=min_samples)
        labels = dbscan.fit_predict(scaled_features)

        # Skip if there's only one cluster
        if len(set(labels)) == 1:
            continue

        # Evaluate silhouette score
        silhouette = silhouette_score(scaled_features, labels)

        # Print the combination and silhouette score
        print(f"eps={eps:.2f}, min_samples={min_samples}, Silhouette Score: {silhouette}")

        # Update best parameters if silhouette score is higher
        if silhouette > best_silhouette_score:
            best_silhouette_score = silhouette
            best_eps = eps
            best_min_samples = min_samples

# Print the best configuration
print(f"Best configuration: eps={best_eps:.2f}, min_samples={best_min_samples}, Silhouette Score: {best_silhouette_score}")
```

In [ ]:
```
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Select features for clustering
features_for_clustering = df[['Purchase_Amount', 'Age', 'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score', 'Average_Spending_Per_Purchase']]

# Standardize the features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features_for_clustering)

# Apply DBSCAN with chosen parameters
eps = 1.2
min_samples = 9

dbscan = DBSCAN(eps=eps, min_samples=min_samples)
labels = dbscan.fit_predict(scaled_features)

# Visualize clusters in 2D using PCA
pca = PCA(n_components=2)
reduced_data = pca.fit_transform(scaled_features)

plt.figure(figsize=(10, 6))
plt.scatter(reduced_data[:, 0], reduced_data[:, 1], c=labels, cmap='viridis')
```

```python
plt.title('DBSCAN Clusters')
plt.xlabel('PCA Feature 1')
plt.ylabel('PCA Feature 2')
plt.show()

# Visualize Purchase_Amount across clusters
sns.barplot(x=labels, y='Purchase_Amount', data=df)
plt.title('Average Purchase Amount Across DBSCAN Clusters')
plt.show()

# Visualize Brand_Affinity_Score across clusters
sns.barplot(x=labels, y='Brand_Affinity_Score', data=df)
plt.title('Average Brand Affinity Score Across DBSCAN Clusters')
plt.show()
```

In [ ]:

```python
from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score

kmeans_silhouette = silhouette_score(scaled_features, df['Cluster_Labels'])
kmeans_calinski_harabasz = calinski_harabasz_score(scaled_features, df['Cluster_Labels'])
kmeans_davies_bouldin = davies_bouldin_score(scaled_features, df['Cluster_Labels'])

kmeansplus_silhouette = silhouette_score(scaled_features, df['Cluster_Labels++'])
kmeansplus_calinski_harabasz = calinski_harabasz_score(scaled_features, df['Cluster_Labels++'])
kmeansplus_davies_bouldin = davies_bouldin_score(scaled_features, df['Cluster_Labels++'])

# Assuming 'labels' are the DBSCAN cluster labels
# Evaluate DBSCAN clustering quality
dbscan_silhouette = silhouette_score(scaled_features, df['Cluster_LabelsDB'])
dbscan_calinski_harabasz = calinski_harabasz_score(scaled_features,df['Cluster_LabelsDB'])
dbscan_davies_bouldin = davies_bouldin_score(scaled_features, df['Cluster_LabelsDB'])

# Print the results
print("K-Means Silhouette Score:", kmeans_silhouette)
print("K-Means Calinski-Harabasz Score:", kmeans_calinski_harabasz)
print("K-Means Davies-Bouldin Index:", kmeans_davies_bouldin)

print("K-Meansplus Silhouette Score:", kmeansplus_silhouette)
print("K-Meansplus Calinski-Harabasz Score:", kmeansplus_calinski_harabasz)
print("K-Meansplus Davies-Bouldin Index:", kmeansplus_davies_bouldin)

print("\nDBSCAN Silhouette Score:", dbscan_silhouette)
print("DBSCAN Calinski-Harabasz Score:", dbscan_calinski_harabasz)
print("DBSCAN Davies-Bouldin Index:", dbscan_davies_bouldin)
```

Module 4

1. Compare the results of all three clustering algorithms:

Number of Iterations:

Regular K-Means: 20 iterations K-Means++: 38 iterations

In terms of convergence speed, Regular K-Means outperforms K-Means++, converging in 20 iterations compared to the 38 iterations taken by K-Means++.

Silhouette Scores:

Silhouette Score for Regular K-Means: 0.0179 Silhouette Score for K-Means++: 0.1590

While both algorithms produce relatively low silhouette scores, indicating moderate cluster quality, K-Means++ demonstrates a slight improvement with a score of 0.159 compared to Regular K-Means with a score of 0.0179.

Conclusion:

Considering the trade-off between convergence speed and cluster quality, the choice between Regular K-Means and K-Means++ depends on specific priorities. Regular K-Means is more computationally efficient, converging faster, but at the cost of slightly lower cluster quality. On the other hand, K-Means++ takes more iterations to converge but offers a marginal improvement in cluster quality. The decision should be guided by the particular requirements of your task, considering factors such as dataset size, computational resources, and the importance of achieving distinct clusters.

Consider metrics such as cluster silhouette score, Calinski-Harabasz score, and Davies-Bouldin index to compare the overall quality of clustering results.

K-Means:

Silhouette Score: 0.0179

Indicates relatively low cohesion and separation among clusters.

Calinski-Harabasz Score: 49.86

Suggests moderate cluster quality, considering the higher values indicate better-defined clusters.

Davies-Bouldin Index: 6.15

Indicates a moderate level of cluster separation.

K-Means++:

Silhouette Score: 0.159

Shows a slight improvement in cluster cohesion and separation compared to regular K-Means.

Calinski-Harabasz Score: 152.05

Suggests better-defined clusters compared to regular K-Means.

Davies-Bouldin Index: 1.52

Indicates a lower level of cluster separation compared to regular K-Means.

DBSCAN:

Silhouette Score: -0.0329

Indicates poor cluster quality, as a negative value suggests significant overlap between clusters.

Calinski-Harabasz Score: 2.71

Suggests lower-quality clusters compared to K-Means and K-Means++.

Davies-Bouldin Index: 1.15

Indicates moderate cluster separation, but the negative silhouette score raises concerns about the effectiveness of DBSCAN for this dataset.

Discuss the advantages and disadvantages of each algorithm in the contextof Imtiaz Mall's specific needs and data characteristics.

From the characteristics of the data—skewed distribution, no outliers, and a moderate-sized dataset—both K-Means and K-Means++ are reasonable choices. DBSCAN, with appropriate parameter tuning, can also be effective, especially when the number of clusters is not known in advance

2. Draw conclusions and recommendations:

part1

age 0-20 and age 30-50 buy electronics brand A in more quantity as compared to other age groups but the affinity score of brand A from these age groups is not according to the sale ,which means that they gave low affinity score to brand A.

age 0-20 and age 30-50 buy electronics brand B in less quantity as compared to brand A but the affinity score of brand B from these age groups is more as compared to Brand A ,which means that they gave high affinity score to brand B.

we checked the behaviour of customers,the customer with high income level bought more products from electronics brand A , the customer with medium income level bought more products from electronics brand B ,the customer with low income level bought more products from electronics brand B.

brand B has more affinity score as compared to other brands now they should start compaign on brand B so that they can have more sale and they must improve quality of brand A because customers bought brand A in more quantity ,if they do not improve quality of brand A then customers will be disappointed and sales of brand A will be declined.

conclusion

from above statements we conclude that sale of brand A is more but affinity score is less and sale of brand B is less as compared to brand A . products and quality of brand A is not good as it should be but quality of brand B is good as compared to barnd A but there affinity score is good that means they have good products in brand B

if imtiaz mall want to increase the sale in electronics product they must improve the quality of brand A as this is not good

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