In [15]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

In [18]:
```python
# Dataset Load
customers = pd.read_csv('C:/Users/avina/Downloads/Zeotap_Assignment/Customers.csv')
products = pd.read_csv('C:/Users/avina/Downloads/Zeotap_Assignment/Products.csv')
transactions = pd.read_csv('C:/Users/avina/Downloads/Zeotap_Assignment/Transactions
```

In [19]:
```python
#Few rows
print("Customers:")
print(customers.head(), '\n')
print("Products:")
print(products.head(), '\n')
print("Transactions:")
print(transactions.head(), '\n')
```

```
Customers:
  CustomerID        CustomerName         Region  SignupDate
0      C0001     Lawrence Carroll  South America  2022-07-10
1      C0002       Elizabeth Lutz           Asia  2022-02-13
2      C0003       Michael Rivera  South America  2024-03-07
3      C0004    Kathleen Rodriguez  South America  2022-10-09
4      C0005          Laura Weber           Asia  2022-08-15

Products:
  ProductID              ProductName     Category   Price
0      P001      ActiveWear Biography        Books  169.30
1      P002     ActiveWear Smartwatch  Electronics  346.30
2      P003    ComfortLiving Biography        Books   44.12
3      P004              BookWorld Rug   Home Decor   95.69
4      P005            TechPro T-Shirt     Clothing  429.31

Transactions:
  TransactionID CustomerID ProductID      TransactionDate  Quantity  \
0        T00001      C0199      P067  2024-08-25 12:38:23         1
1        T00112      C0146      P067  2024-05-27 22:23:54         1
2        T00166      C0127      P067  2024-04-25 07:38:55         1
3        T00272      C0087      P067  2024-03-26 22:55:37         2
4        T00363      C0070      P067  2024-03-21 15:10:10         3

   TotalValue   Price
0      300.68  300.68
1      300.68  300.68
2      300.68  300.68
3      601.36  300.68
4      902.04  300.68
```

In [20]:
```python
#Data Inspection
print(customers.info())
print(products.info())
print(transactions.info())
```

```
#Check null values
print(customers.isnull().sum())
print(products.isnull().sum())
print(transactions.isnull().sum())

#Summary
print(transactions.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   CustomerID    200 non-null    object
 1   CustomerName  200 non-null    object
 2   Region        200 non-null    object
 3   SignupDate    200 non-null    object
dtypes: object(4)
memory usage: 6.4+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   ProductID    100 non-null    object 
 1   ProductName  100 non-null    object 
 2   Category     100 non-null    object 
 3   Price        100 non-null    float64
dtypes: float64(1), object(3)
memory usage: 3.3+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   TransactionID    1000 non-null   object 
 1   CustomerID       1000 non-null   object 
 2   ProductID        1000 non-null   object 
 3   TransactionDate  1000 non-null   object 
 4   Quantity         1000 non-null   int64  
 5   TotalValue       1000 non-null   float64
 6   Price            1000 non-null   float64
dtypes: float64(2), int64(1), object(4)
memory usage: 54.8+ KB
None
CustomerID      0
CustomerName    0
Region          0
SignupDate      0
dtype: int64
ProductID      0
ProductName    0
Category       0
Price          0
dtype: int64
TransactionID      0
CustomerID         0
ProductID          0
TransactionDate    0
Quantity           0
TotalValue         0
Price              0
```

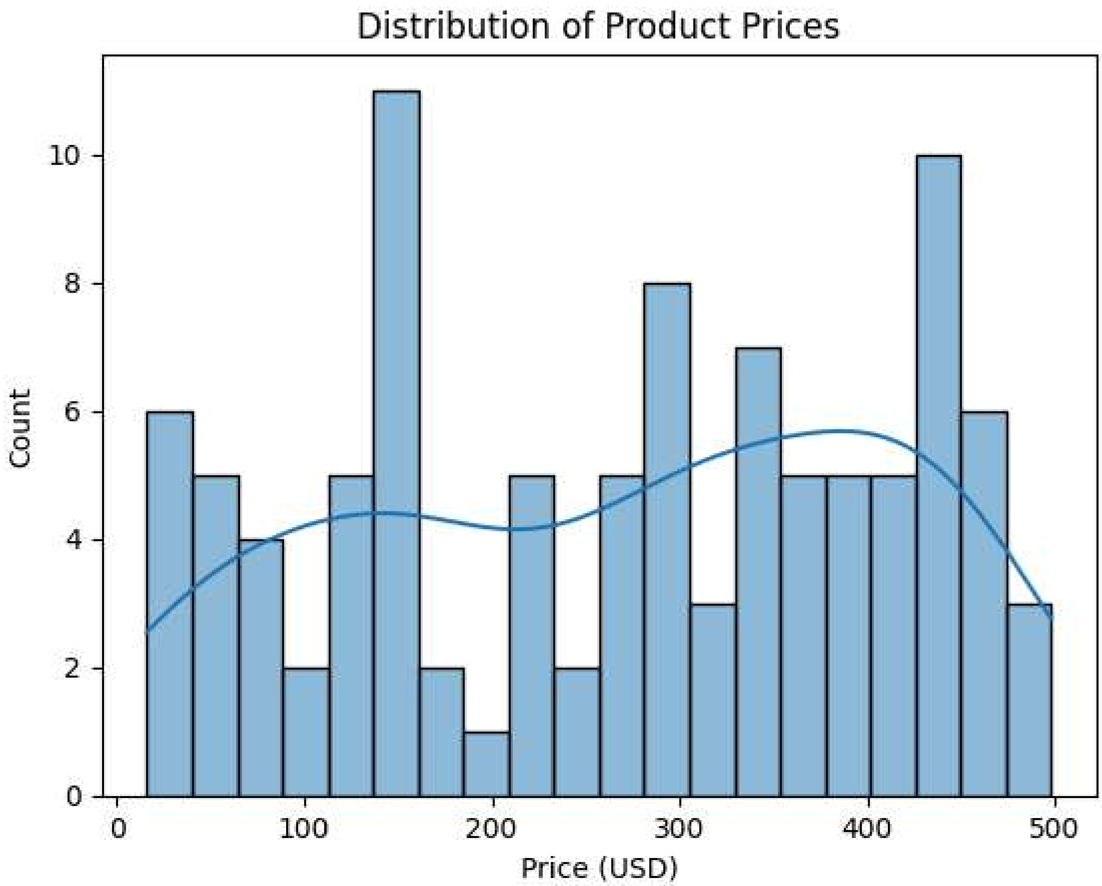
```
dtype: int64
          Quantity   TotalValue        Price
count  1000.000000  1000.000000  1000.00000
mean      2.537000   689.995560   272.55407
std       1.117981   493.144478   140.73639
min       1.000000    16.080000    16.08000
25%       2.000000   295.295000   147.95000
50%       3.000000   588.880000   299.93000
75%       4.000000  1011.660000   404.40000
max       4.000000  1991.040000   497.76000
```

In [60]:

```python
# Visualizations_1
# Signups (By region)
sns.countplot(data=customers, x='Region', hue='Region', palette='viridis', legend=F
plt.title('Number of Customers by Region')
plt.show()
```

In [22]:

```python
#Visualization_2
#Product prices distribution
sns.histplot(data=products, x='Price', bins=20, kde=True)
plt.title('Distribution of Product Prices')
plt.xlabel('Price (USD)')
plt.show()
```



In [26]:

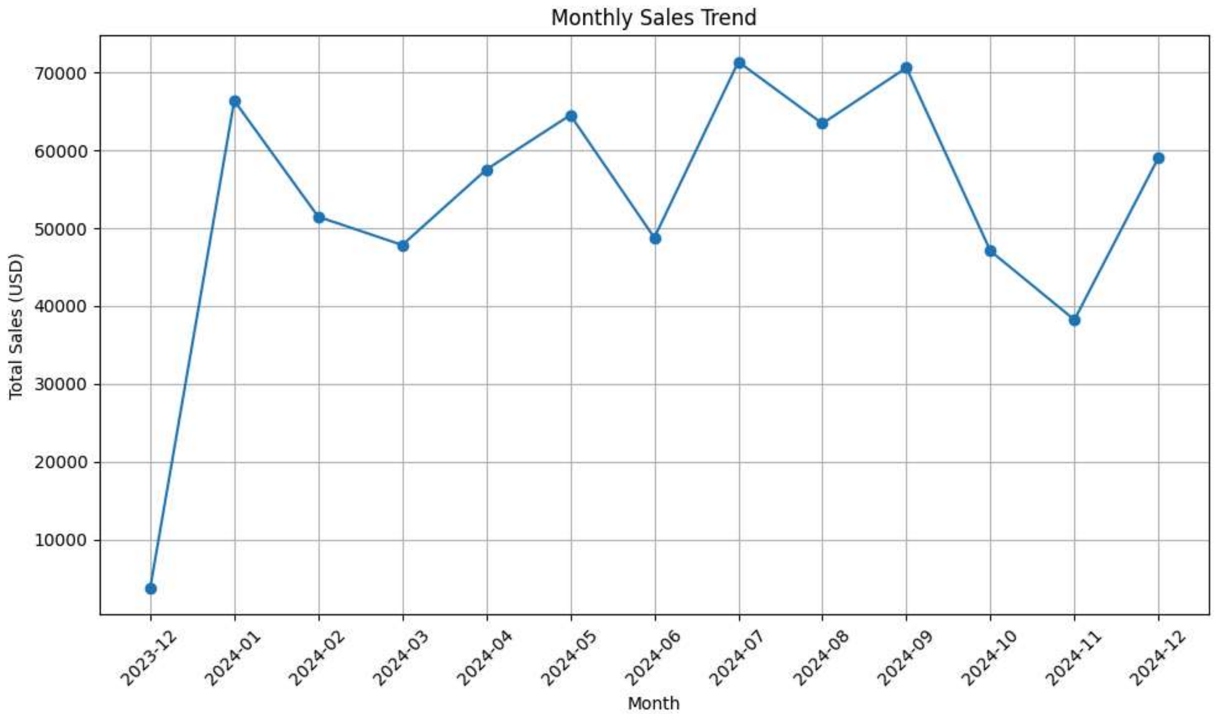
```
#Visualization_3
#Transactions v/s time

transactions['TransactionDate'] = pd.to_datetime(transactions['TransactionDate'])

transactions['Month'] = transactions['TransactionDate'].dt.to_period('M')

monthly_sales = transactions.groupby('Month')['TotalValue'].sum()

# Plot the monthly sales trend
plt.figure(figsize=(10, 6))
plt.plot(monthly_sales.index.astype(str), monthly_sales.values, marker='o')
plt.title('Monthly Sales Trend')
plt.xlabel('Month')
plt.ylabel('Total Sales (USD)')
plt.xticks(rotation=45)
plt.grid()
plt.tight_layout()
plt.show()
```



In [29]:
```
# Prepare data by merging datasets

#MERGING DATASETS

data = transactions.merge(customers, on='CustomerID').merge(products, on='ProductID

print(data.columns)

#Profile creation of each customer
customer_profiles = data.groupby('CustomerID').agg({
    # Average product price purchased
    'Price_y': 'mean',
     # Total quantity purchased
    'Quantity': 'sum',
    # Total spend
    'TotalValue': 'sum'
}).reset_index()

print(customer_profiles.head())
```

```
Index(['TransactionID', 'CustomerID', 'ProductID', 'TransactionDate',
       'Quantity', 'TotalValue', 'Price_x', 'Month', 'CustomerName', 'Region',
       'SignupDate', 'ProductName', 'Category', 'Price_y'],
      dtype='object')
  CustomerID     Price_y  Quantity  TotalValue
0      C0001  278.334000        12     3354.52
1      C0002  208.920000        10     1862.74
2      C0003  195.707500        14     2725.38
3      C0004  240.636250        23     5354.88
4      C0005  291.603333         7     2034.24
```

In [32]:
```
#Similarity Calculation (cosine similarity)

import os
```

```python
import csv
from sklearn.metrics.pairwise import cosine_similarity
import pandas as pd

# Assumed -> Customer_profiles DataFrame already created

# Prepare the input features: we can use average price, total spend, total quantity
X = customer_profiles[['Price_y', 'Quantity', 'TotalValue']].values

# Compute cosine similarity
similarity_matrix = cosine_similarity(X)
results = {}

# Iterate over customers to find their lookalikes
for i, customer_id in enumerate(customer_profiles['CustomerID']):

    similarities = list(enumerate(similarity_matrix[i]))
    similarities = sorted(similarities, key=lambda x: x[1], reverse=True)[1:4]

    results[customer_id] = [(customer_profiles.iloc[idx, 0], round(score, 2)) for i

os.makedirs('outputs', exist_ok=True)

with open('outputs/Lookalike.csv', 'w', newline='') as f:
    writer = csv.writer(f)
    writer.writerow(['CustomerID', 'Lookalikes'])

    for customer_id, lookalikes in results.items():
        # Format the list of lookalikes for writing
        lookalike_str = ', '.join([f'{lookalike[0]} ({lookalike[1]})' for lookalike
        writer.writerow([customer_id, lookalike_str])

print("Lookalike model results written to 'outputs/Lookalike.csv'")
```

```
Lookalike model results written to 'outputs/Lookalike.csv'
```

In [39]:

```python
print(data.columns)
```

```
Index(['TransactionID', 'CustomerID', 'ProductID', 'TransactionDate',
       'Quantity', 'TotalValue', 'Price_x', 'Month', 'CustomerName', 'Region',
       'SignupDate', 'ProductName', 'Category', 'Price_y'],
      dtype='object')
```

In [45]:

```python
print(data.head())
```

```
  TransactionID CustomerID ProductID      TransactionDate  Quantity  \
0        T00001      C0199      P067  2024-08-25 12:38:23         1
1        T00112      C0146      P067  2024-05-27 22:23:54         1
2        T00166      C0127      P067  2024-04-25 07:38:55         1
3        T00272      C0087      P067  2024-03-26 22:55:37         2
4        T00363      C0070      P067  2024-03-21 15:10:10         3

   TotalValue  Price_x    Month      CustomerName         Region  SignupDate  \
0      300.68   300.68  2024-08   Andrea Jenkins         Europe  2022-12-03
1      300.68   300.68  2024-05  Brittany Harvey           Asia  2024-09-04
2      300.68   300.68  2024-04  Kathryn Stevens         Europe  2024-04-04
3      601.36   300.68  2024-03  Travis Campbell  South America  2024-04-11
4      902.04   300.68  2024-03    Timothy Perez         Europe  2022-03-15

                       ProductName     Category  Price_y
0  ComfortLiving Bluetooth Speaker  Electronics   300.68
1  ComfortLiving Bluetooth Speaker  Electronics   300.68
2  ComfortLiving Bluetooth Speaker  Electronics   300.68
3  ComfortLiving Bluetooth Speaker  Electronics   300.68
4  ComfortLiving Bluetooth Speaker  Electronics   300.68
```

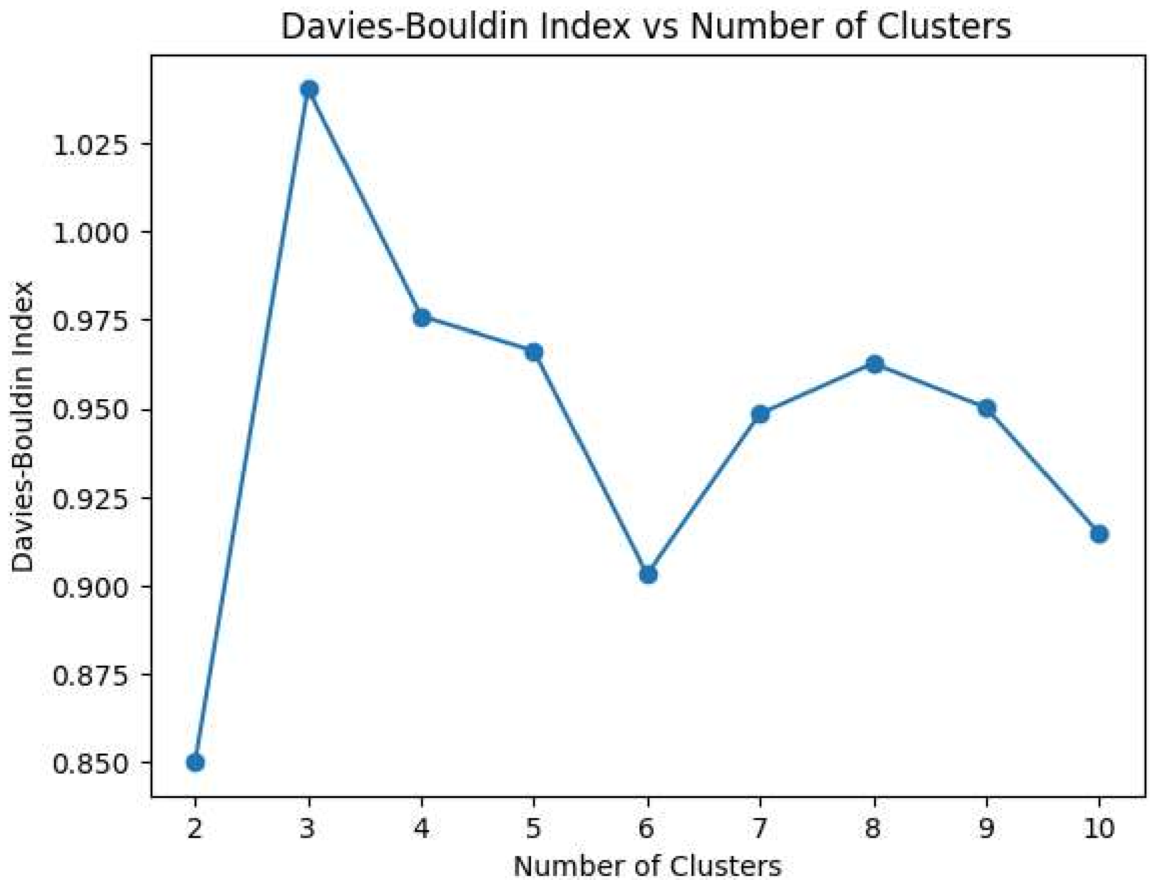
In [46]:

```python
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score

# Davies-Bouldin Index
# Optimal number of clusters
scores = []
# Check for k from 2 to 10
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    clusters = kmeans.fit_predict(features)
    score = davies_bouldin_score(features, clusters)
    scores.append(score)

# Plot Index for each k
plt.plot(range(2, 11), scores, marker='o')
plt.title('Davies-Bouldin Index vs Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Davies-Bouldin Index')
plt.show()

#  lowest Davies-Bouldin index with one optimal k
optimal_k = scores.index(min(scores)) + 2
print(f"Optimal number of clusters: {optimal_k}")
```




```
Optimal number of clusters: 2
```

In [47]:
```
# Apply K-Means with optimal number of clusters
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
customer_profiles['Cluster'] = kmeans.fit_predict(features)

print(customer_profiles.head())
```

```
  CustomerID     Price_y  Quantity  TotalValue  Cluster
0      C0001  278.334000        12     3354.52        1
1      C0002  208.920000        10     1862.74        1
2      C0003  195.707500        14     2725.38        1
3      C0004  240.636250        23     5354.88        0
4      C0005  291.603333         7     2034.24        1
```

In [58]:
```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# 2D for visualization
pca = PCA(n_components=2)
reduced_features = pca.fit_transform(features)

# DataFrame to hold the 2D PCA components and cluster labels
customer_profiles['PCA1'] = reduced_features[:, 0]
customer_profiles['PCA2'] = reduced_features[:, 1]

# Get unique clusters
unique_clusters = customer_profiles['Cluster'].nunique()
```

```
# Define marker styles based on the number of clusters
markers = ['o', 's', 'D', 'X', 'P', '^', 'v', '<', '>'][:unique_clusters]

# Plot the clusters
plt.figure(figsize=(9,6))

# Use Seaborn's scatterplot with dynamic markers
sns.scatterplot(data=customer_profiles, x='PCA1', y='PCA2', hue='Cluster', palette=
                style='Cluster', markers=markers, s=100, edgecolor='black', legend=

# Adding titles and labels for clarity
plt.title('Customer Segmentation with K-Means Clustering', fontsize=16)
plt.xlabel('PCA Component 1', fontsize=12)
plt.ylabel('PCA Component 2', fontsize=12)

# Display the legend
plt.legend(title='Cluster', bbox_to_anchor=(1.05, 1), loc='upper left')

# Show the plot with a clean layout
plt.tight_layout()
plt.show()
```

In [49]:
```
# Calculate final Davies-Bouldin Index
db_index = davies_bouldin_score(features, customer_profiles['Cluster'])
print(f"Davies-Bouldin Index for the final clustering: {db_index}")
```

```
Davies-Bouldin Index for the final clustering: 0.8502362410640188
```

In [ ]: