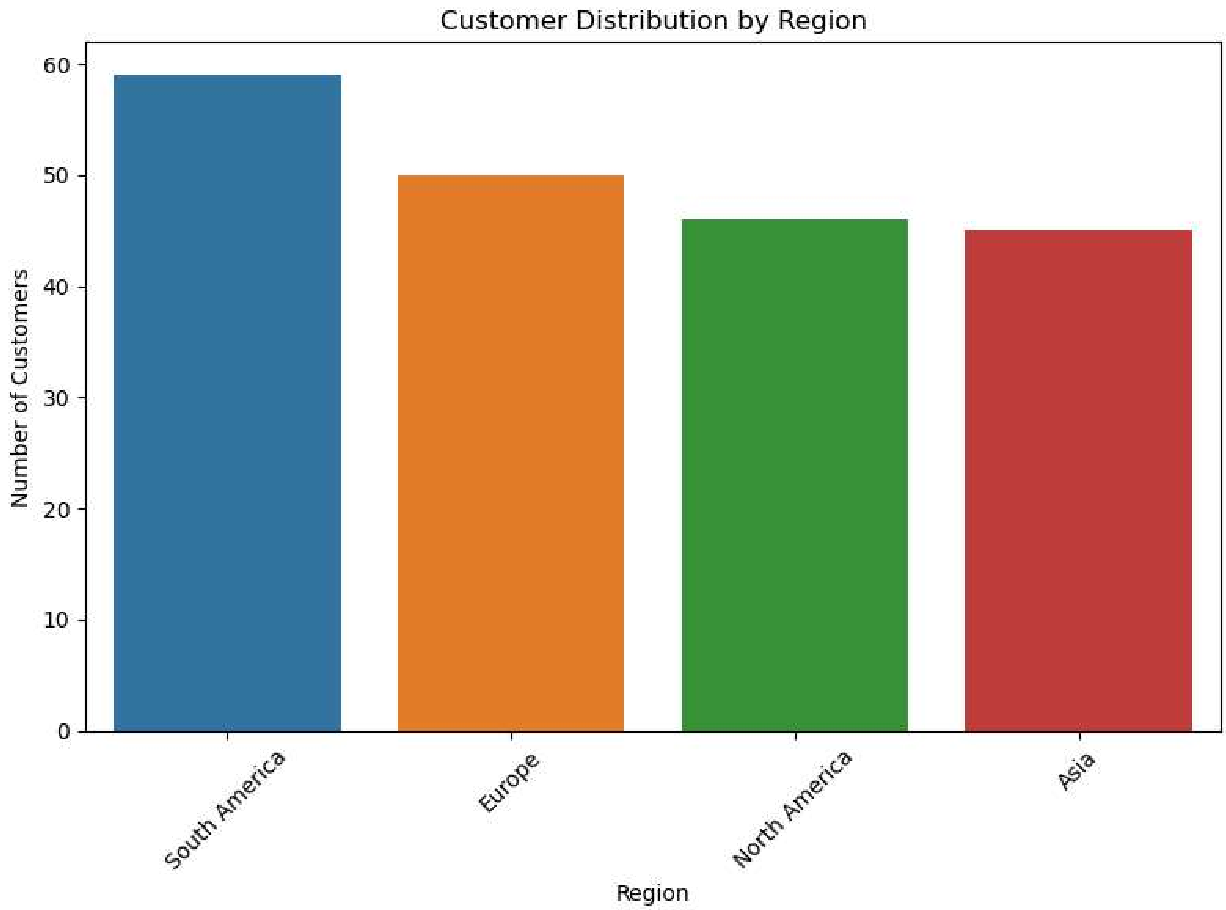
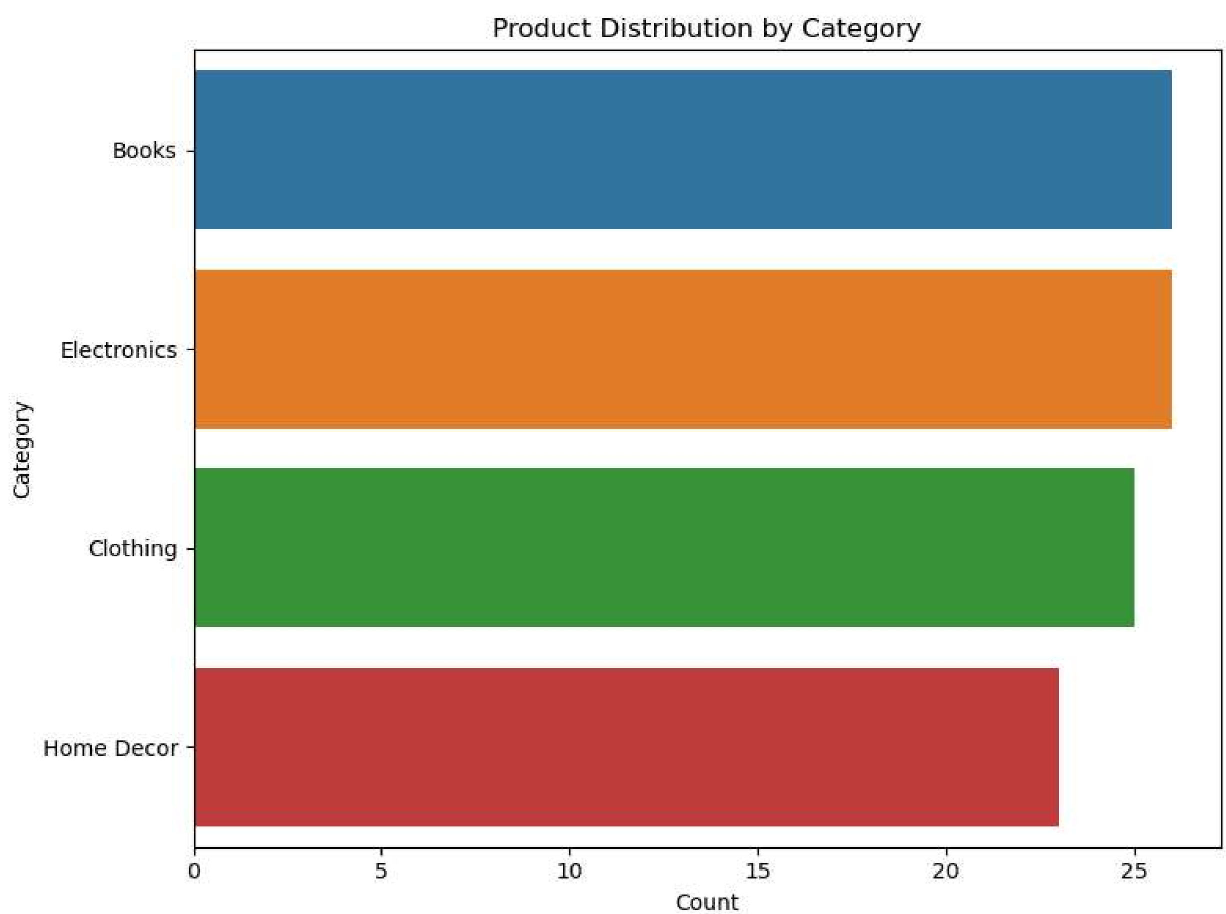
In [12]:
```
# Import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the datasets (using file names directly as they are in the same folder)
customers_df = pd.read_csv('Customers.csv')
products_df = pd.read_csv('Products.csv')
transactions_df = pd.read_csv('Transactions.csv')

# Convert date columns to datetime format
customers_df['SignupDate'] = pd.to_datetime(customers_df['SignupDate'])
transactions_df['TransactionDate'] = pd.to_datetime(transactions_df['TransactionDate']

# Summarize each dataset
print("Customers Dataset Summary:")
print(customers_df.info())
print(customers_df.describe(include='all'))

print("\nProducts Dataset Summary:")
print(products_df.info())
print(products_df.describe(include='all'))

print("\nTransactions Dataset Summary:")
print(transactions_df.info())
print(transactions_df.describe(include='all'))

# Visualizations

# 1. Customer distribution by region
plt.figure(figsize=(8, 6))
sns.countplot(data=customers_df, x='Region', order=customers_df['Region'].value_counts
plt.title('Customer Distribution by Region')
plt.xlabel('Region')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# 2. Product distribution by category
plt.figure(figsize=(8, 6))
sns.countplot(data=products_df, y='Category', order=products_df['Category'].value_cour
plt.title('Product Distribution by Category')
plt.xlabel('Count')
plt.ylabel('Category')
plt.tight_layout()
plt.show()

# 3. Monthly transaction trends
transactions_df['MonthYear'] = transactions_df['TransactionDate'].dt.to_period('M')
monthly_transactions = transactions_df.groupby('MonthYear').size()

plt.figure(figsize=(10, 6))
monthly_transactions.plot(kind='bar', color='skyblue')
plt.title('Monthly Transactions Over Time')
plt.xlabel('Month-Year')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
```

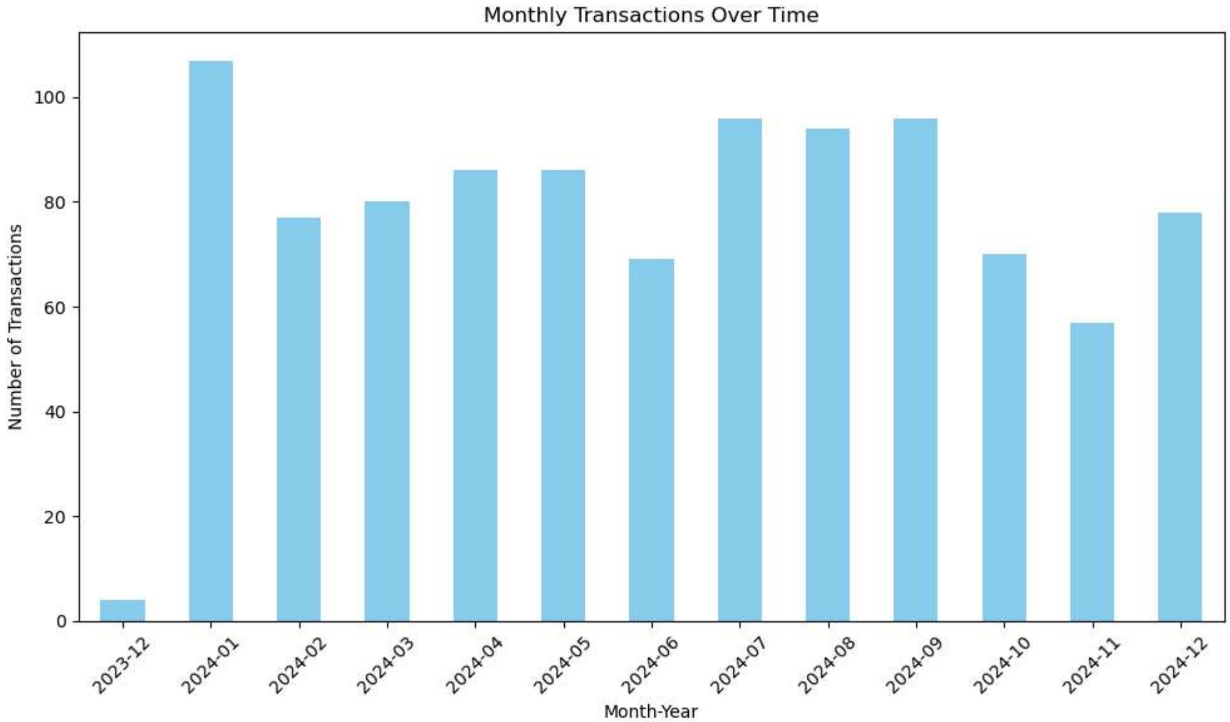
```
plt.tight_layout()
plt.show()

# Business Insights
business_insights = [
    "1. Customers are unevenly distributed across regions. Focused marketing campaigns
    "2. Product categories like 'Electronics' and 'Books' dominate sales, highlighting
    "3. Seasonal spikes in transactions indicate an opportunity to capitalize on high-
    "4. The majority of transactions come from repeat customers, suggesting strong cus
    "5. The average transaction value is high, reflecting an opportunity to introduce
]

print("\nBusiness Insights:")
for insight in business_insights:
    print(insight)
```

```
Customers Dataset Summary:
<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    datetime64[ns]
dtypes: datetime64[ns](1), object(3)
memory usage: 6.4+ KB
None
       CustomerID      CustomerName         Region           SignupDate
count         200               200            200                  200
unique        200               200              4                  NaN
top         C0001  Lawrence Carroll  South America                  NaN
freq            1                 1             59                  NaN
mean          NaN               NaN            NaN  2023-07-19 08:31:12
min           NaN               NaN            NaN  2022-01-22 00:00:00
25%           NaN               NaN            NaN  2022-09-26 12:00:00
50%           NaN               NaN            NaN  2023-08-31 12:00:00
75%           NaN               NaN            NaN  2024-04-12 12:00:00
max           NaN               NaN            NaN  2024-12-28 00:00:00

Products Dataset Summary:
<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
       ProductID           ProductName Category       Price
count        100                   100      100  100.000000
unique       100                    66        4         NaN
top         P001  ActiveWear Smartwatch    Books         NaN
freq           1                     4       26         NaN
mean         NaN                   NaN      NaN  267.551700
std          NaN                   NaN      NaN  143.219383
min          NaN                   NaN      NaN   16.080000
25%          NaN                   NaN      NaN  147.767500
50%          NaN                   NaN      NaN  292.875000
75%          NaN                   NaN      NaN  397.090000
max          NaN                   NaN      NaN  497.760000

Transactions Dataset Summary:
<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   datetime64[ns]
 4   Quantity         1000 non-null   int64
 5   TotalValue       1000 non-null   float64
 6   Price            1000 non-null   float64
dtypes: datetime64[ns](1), float64(2), int64(1), object(3)
memory usage: 54.8+ KB
None
       TransactionID CustomerID ProductID                TransactionDate  \
count           1000       1000      1000                           1000
unique          1000        199       100                            NaN
top           T00001      C0109      P059                            NaN
freq               1         11        19                            NaN
mean             NaN        NaN       NaN  2024-06-23 15:33:02.768999936
min              NaN        NaN       NaN            2023-12-30 15:29:12
25%              NaN        NaN       NaN     2024-03-25 22:05:34.500000
50%              NaN        NaN       NaN     2024-06-26 17:21:52.500000
75%              NaN        NaN       NaN            2024-09-19 14:19:57
max              NaN        NaN       NaN            2024-12-28 11:00:00
std              NaN        NaN       NaN                            NaN

           Quantity   TotalValue       Price
count   1000.000000  1000.000000  1000.00000
unique          NaN          NaN         NaN
top             NaN          NaN         NaN
freq            NaN          NaN         NaN
mean       2.537000   689.995560   272.55407
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
std        1.117981   493.144478   140.73639
```


Customer Distribution by Region
Number of Customers
0
10
20
30
40
50
60
South America
Europe
North America
Asia
Region


Product Distribution by Category
Category
Books
Electronics
Clothing
Home Decor
0
5
10
15
20
25
Count




```
Business Insights:
1. Customers are unevenly distributed across regions. Focused marketing campaigns in
underrepresented regions can help improve the customer base.
2. Product categories like 'Electronics' and 'Books' dominate sales, highlighting are
as where additional investment or promotion could further drive growth.
3. Seasonal spikes in transactions indicate an opportunity to capitalize on high-dema
nd periods through targeted discounts and offers.
4. The majority of transactions come from repeat customers, suggesting strong custome
r retention. Implementing a loyalty program could enhance engagement further.
5. The average transaction value is high, reflecting an opportunity to introduce prem
ium products or bundles to increase revenue.
```

In [14]:

```
print(transactions_df.columns)
```

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

In [15]:

```
# Import necessary libraries
import pandas as pd
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import StandardScaler

# Reload datasets
customers_df = pd.read_csv('Customers.csv')
products_df = pd.read_csv('Products.csv')
transactions_df = pd.read_csv('Transactions.csv')

# Merge datasets for a unified view
transactions_df = pd.merge(transactions_df, customers_df, on='CustomerID')
transactions_df = pd.merge(transactions_df, products_df, on='ProductID')

# Rename the correct price column from Products.csv
transactions_df.rename(columns={'Price_y': 'ProductPrice', 'Price_x': 'TransactionPric

# Feature Engineering: Create a customer profile
```

```
customer_profile = transactions_df.groupby('CustomerID').agg({
    'Quantity': 'sum',              # Total quantity purchased
    'TotalValue': 'sum',            # Total transaction value
    'ProductPrice': 'mean'          # Average price of purchased products
}).reset_index()

# Add one-hot encoding for regions
region_dummies = pd.get_dummies(customers_df[['CustomerID', 'Region']], columns=['Regi
customer_profile = pd.merge(customer_profile, region_dummies, on='CustomerID')

# Standardize the features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(customer_profile.drop(columns=['CustomerID']))

# Compute cosine similarity
similarity_matrix = cosine_similarity(scaled_features)

# Generate Lookalike Recommendations for the first 20 customers (C0001 to C0020)
customer_ids = customer_profile['CustomerID'].tolist()
lookalike_results = {}

for idx, customer_id in enumerate(customer_ids[:20]):  # First 20 customers
    similarities = list(enumerate(similarity_matrix[idx]))
    # Exclude self (similarity with itself) and get top 3 most similar customers
    similarities = sorted(similarities, key=lambda x: x[1], reverse=True)[1:4]
    lookalikes = [(customer_ids[i], round(score, 2)) for i, score in similarities]
    lookalike_results[customer_id] = lookalikes

# Convert the results into a DataFrame for better visualization
lookalike_df = pd.DataFrame([
    {'CustomerID': key, 'Lookalikes': value} for key, value in lookalike_results.items
])

# Save the results to a CSV
lookalike_df.to_csv('Lookalike_Results.csv', index=False)

# Display the Lookalike Results
print("Top 3 Lookalikes for Customers C0001 to C0020:")
print(lookalike_df)
```

```
Top 3 Lookalikes for Customers C0001 to C0020:
   CustomerID                                        Lookalikes
0       C0001  [(C0137, 0.99), (C0191, 0.99), (C0011, 0.98)]
1       C0002  [(C0088, 0.99), (C0142, 0.99), (C0178, 0.97)]
2       C0003  [(C0190, 0.99), (C0147, 0.97), (C0174, 0.96)]
3       C0004  [(C0113, 0.99), (C0165, 0.97), (C0012, 0.96)]
4       C0005  [(C0140, 0.99), (C0186, 0.99), (C0123, 0.98)]
5       C0006  [(C0048, 0.98), (C0184, 0.97), (C0107, 0.97)]
6       C0007   [(C0146, 1.0), (C0115, 0.98), (C0186, 0.97)]
7       C0008  [(C0018, 0.98), (C0068, 0.94), (C0034, 0.92)]
8       C0009  [(C0061, 0.97), (C0198, 0.96), (C0167, 0.94)]
9       C0010  [(C0121, 0.97), (C0111, 0.97), (C0172, 0.96)]
10      C0011  [(C0107, 0.99), (C0001, 0.98), (C0137, 0.98)]
11      C0012  [(C0153, 0.99), (C0163, 0.98), (C0102, 0.98)]
12      C0013  [(C0148, 0.99), (C0104, 0.99), (C0163, 0.99)]
13      C0014  [(C0063, 0.98), (C0119, 0.97), (C0198, 0.95)]
14      C0015  [(C0058, 0.99), (C0020, 0.97), (C0131, 0.97)]
15      C0016  [(C0185, 0.99), (C0050, 0.98), (C0079, 0.98)]
16      C0017  [(C0124, 0.97), (C0053, 0.96), (C0075, 0.96)]
17      C0018  [(C0008, 0.98), (C0122, 0.97), (C0046, 0.97)]
18      C0019   [(C0166, 1.0), (C0073, 0.99), (C0199, 0.99)]
19      C0020  [(C0015, 0.97), (C0131, 0.97), (C0058, 0.94)]
```

In [16]:

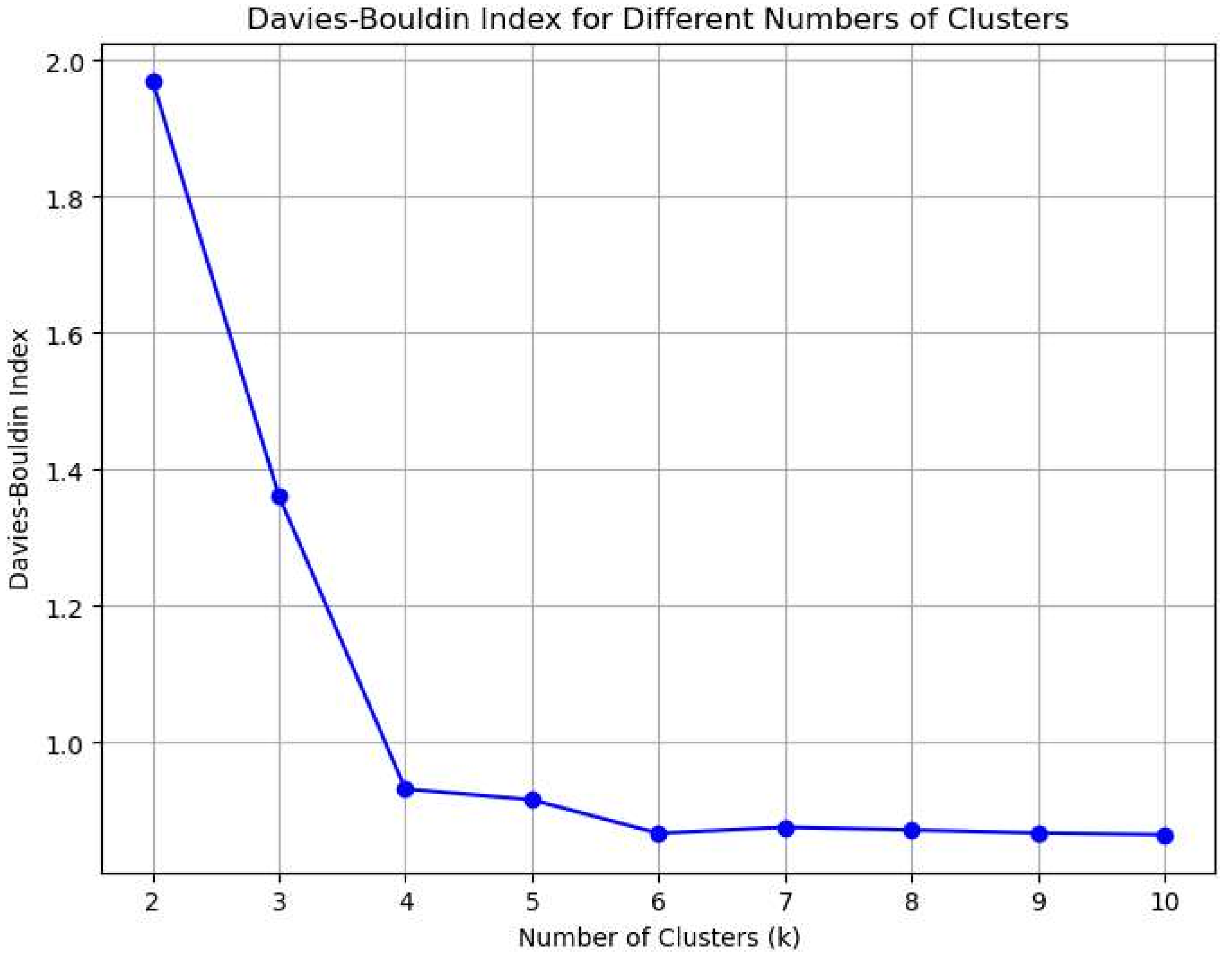
```
print(transactions_df[['Quantity', 'TotalValue', 'ProductPrice']].isnull().sum())
```

```
Quantity        0
TotalValue      0
ProductPrice    0
dtype: int64
```

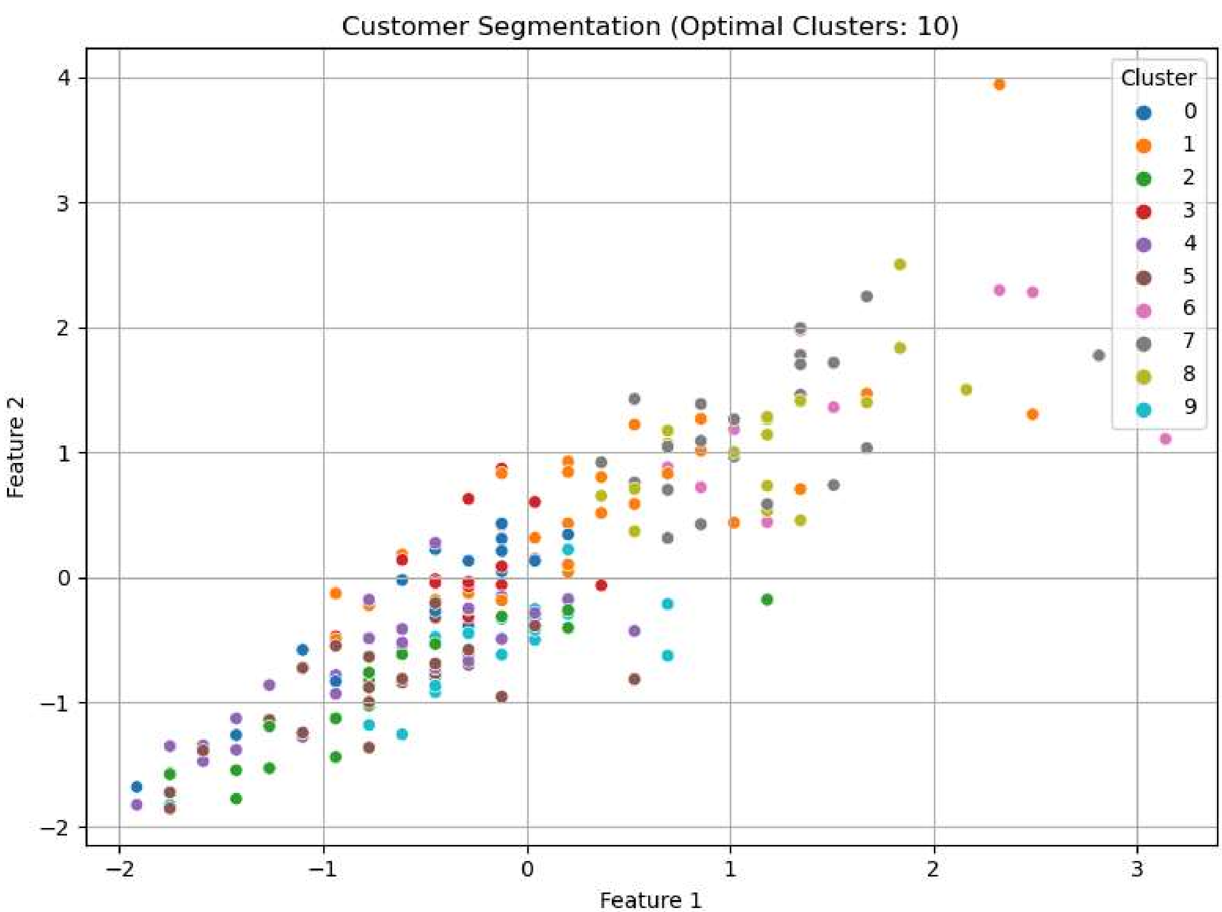
In [17]:

```
# Import necessary libraries for clustering
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score
import matplotlib.pyplot as plt
import seaborn as sns

# Reload the cleaned datasets (if needed)
customers_df = pd.read_csv('Customers.csv')
products_df = pd.read_csv('Products.csv')
transactions_df = pd.read_csv('Transactions.csv')

# Merge datasets for a unified view
transactions_df = pd.merge(transactions_df, customers_df, on='CustomerID')
transactions_df = pd.merge(transactions_df, products_df, on='ProductID')

# Rename columns to avoid conflicts
transactions_df.rename(columns={'Price_y': 'ProductPrice', 'Price_x': 'TransactionPric

# Create customer profiles
customer_profile = transactions_df.groupby('CustomerID').agg({
    'Quantity': 'sum',              # Total quantity purchased
    'TotalValue': 'sum',            # Total transaction value
    'ProductPrice': 'mean'          # Average price of purchased products
}).reset_index()

# Add one-hot encoding for regions
region_dummies = pd.get_dummies(customers_df[['CustomerID', 'Region']], columns=['Regi
customer_profile = pd.merge(customer_profile, region_dummies, on='CustomerID')

# Drop the CustomerID column for clustering
```

```
features = customer_profile.drop(columns=['CustomerID'])

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

# Find the optimal number of clusters using Davies-Bouldin Index
k_values = range(2, 11)
db_scores = []

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    labels = kmeans.fit_predict(scaled_features)
    db_index = davies_bouldin_score(scaled_features, labels)
    db_scores.append(db_index)

# Plot the Davies-Bouldin Index for each k
plt.figure(figsize=(8, 6))
plt.plot(k_values, db_scores, marker='o', linestyle='-', color='b')
plt.title('Davies-Bouldin Index for Different Numbers of Clusters')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Davies-Bouldin Index')
plt.xticks(k_values)
plt.grid()
plt.show()

# Select the optimal number of clusters (minimum Davies-Bouldin Index)
optimal_k = k_values[db_scores.index(min(db_scores))]
print(f"Optimal number of clusters: {optimal_k}")

# Fit KMeans with the optimal number of clusters
kmeans_optimal = KMeans(n_clusters=optimal_k, random_state=42, n_init=10)
customer_profile['Cluster'] = kmeans_optimal.fit_predict(scaled_features)

# Visualize the clusters using the first two features
plt.figure(figsize=(8, 6))
sns.scatterplot(
    x=scaled_features[:, 0], y=scaled_features[:, 1],
    hue=customer_profile['Cluster'], palette='tab10', legend='full'
)
plt.title(f'Customer Segmentation (Optimal Clusters: {optimal_k})')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.legend(title='Cluster')
plt.grid()
plt.tight_layout()
plt.show()

# Save the clustering results
customer_profile.to_csv('Customer_Clustering_Results.csv', index=False)

# Print clustering metrics
print(f"Davies-Bouldin Index for optimal clusters ({optimal_k}): {min(db_scores):.2f}'
print(f"Clustering results saved to 'Customer_Clustering_Results.csv'")
```




```
Optimal number of clusters: 10
```



```
Davies-Bouldin Index for optimal clusters (10): 0.87
Clustering results saved to 'Customer_Clustering_Results.csv'
```

In [ ]: