Task 3: Customer Segmentation / Clustering

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
customers_df = pd.read_csv(r'C:\Users\Bhatta\Downloads\Customers.csv')
products_df = pd.read_csv(r'C:\Users\Bhatta\Downloads\Products.csv')
transactions_df =  pd.read_csv(r'C:\Users\Bhatta\Downloads\Transactions.csv')
```

In [3]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score, silhouette_score
from sklearn.preprocessing import StandardScaler
```

In [4]:
```
# Merge datasets
customer_transactions = pd.merge(transactions_df, customers_df, on="CustomerID", how="left")
customer_transactions = pd.merge(customer_transactions, products_df, on="ProductID", how="left")
```

In [5]:
```
# Feature engineering
customer_features = customer_transactions.groupby("CustomerID").agg(
    total_spent=("TotalValue", "sum"),
    total_transactions=("TransactionID", "count"),
    avg_transaction_value=("TotalValue", "mean"),
    distinct_products=("ProductID", "nunique"),
    total_quantity=("Quantity", "sum")
).reset_index()

customer_features = pd.merge(customer_features, customers_df[["CustomerID", "Region"]], on="CustomerID", how="left")
customer_features = pd.get_dummies(customer_features, columns=["Region"], drop_first=True)
```

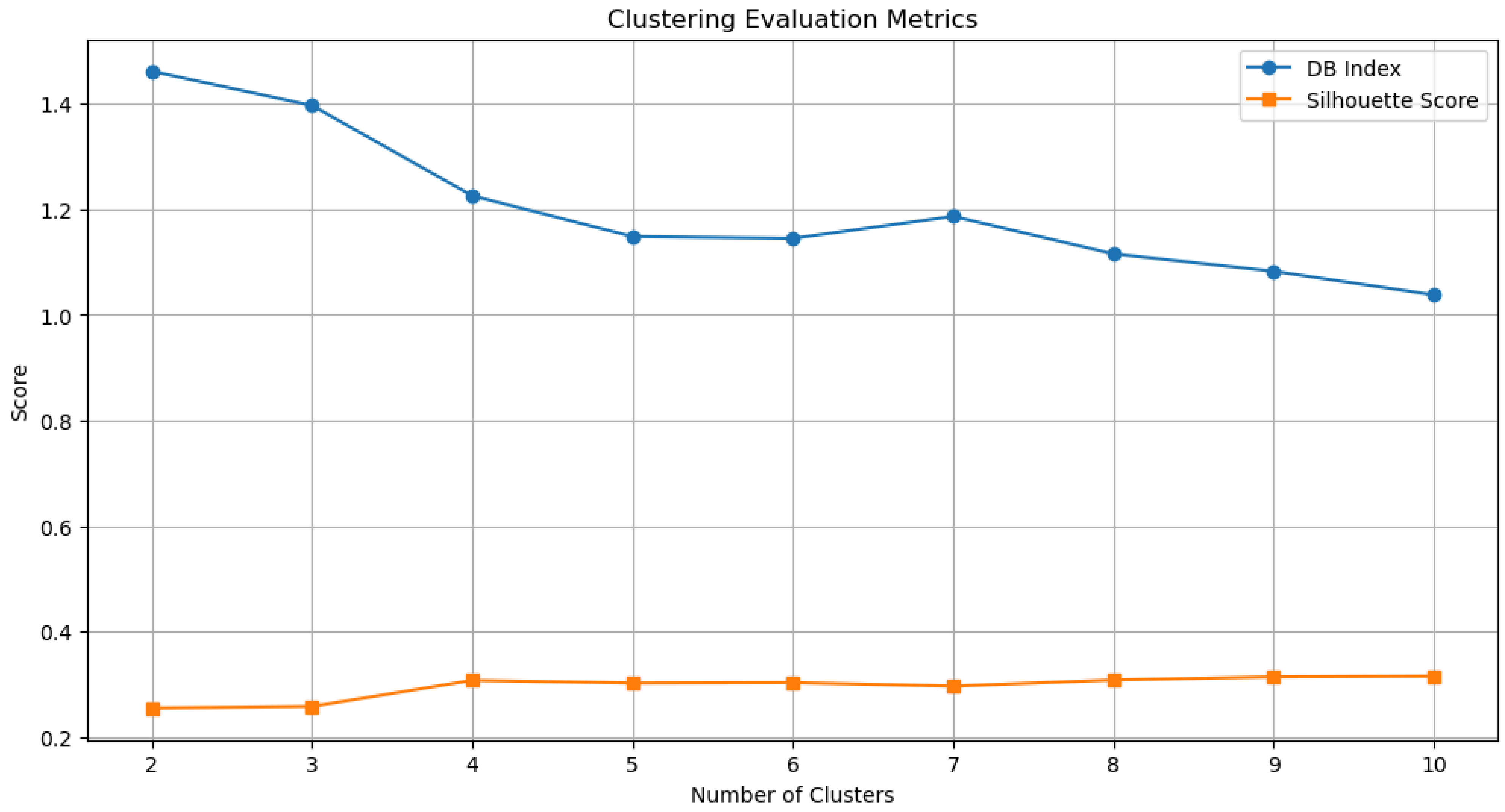
In [6]:
```
# Prepare data for clustering
X = customer_features.drop(columns=["CustomerID"])
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [7]:
```
# Apply KMeans clustering and evaluate using DBI and silhouette score
cluster_results = []
for n_clusters in range(2, 11):
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    labels = kmeans.fit_predict(X_scaled)
    db_index = davies_bouldin_score(X_scaled, labels)
    silhouette_avg = silhouette_score(X_scaled, labels)
    cluster_results.append({
        "n_clusters": n_clusters,
        "DBI": db_index,
        "Silhouette": silhouette_avg,
    })
```

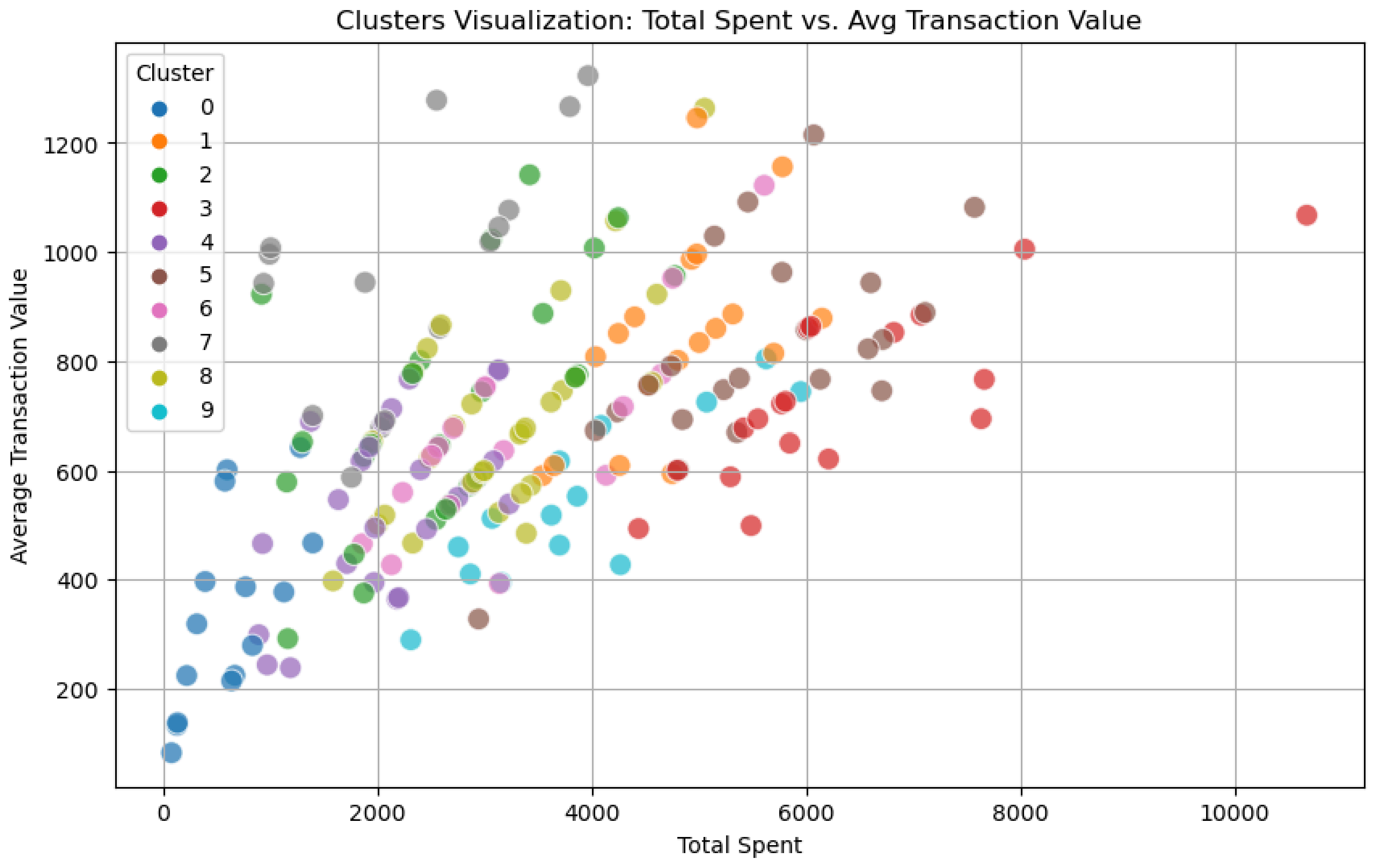
In [8]:
```
# Determine the best number of clusters
best_cluster = min(cluster_results, key=lambda x: x["DBI"])
```

In [9]:
```
# Apply KMeans with the optimal number of clusters
optimal_kmeans = KMeans(n_clusters=best_cluster["n_clusters"], random_state=42)
customer_features["Cluster"] = optimal_kmeans.fit_predict(X_scaled)
```

In [10]:
```
# Visualize DBI and silhouette scores
results_df = pd.DataFrame(cluster_results)
plt.figure(figsize=(12, 6))
plt.plot(results_df["n_clusters"], results_df["DBI"], marker="o", label="DB Index")
plt.plot(results_df["n_clusters"], results_df["Silhouette"], marker="s", label="Silhouette Score")
plt.xlabel("Number of Clusters")
plt.ylabel("Score")
plt.title("Clustering Evaluation Metrics")
plt.legend()
plt.grid()
plt.show()
```



In [11]:
```
# Visualize clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=customer_features,
    x="total_spent",
    y="avg_transaction_value",
    hue="Cluster",
    palette="tab10",
    s=100,
    alpha=0.7
)
plt.title("Clusters Visualization: Total Spent vs. Avg Transaction Value")
plt.xlabel("Total Spent")
plt.ylabel("Average Transaction Value")
plt.legend(title="Cluster")
plt.grid()
plt.show()
```



In [12]:
```
# Summarize clusters
cluster_summary = customer_features.groupby("Cluster").mean()
pd.DataFrame(cluster_summary)
```

Out[12]:

Cluster	total_spent	total_transactions	avg_transaction_value	distinct_products	total_quantity	Region_Europe	Region_North America	Region_South America
0	614.394000	1.800000	337.578667	1.800000	3.533333	0.133333	0.133333	0.533333
1	4792.131111	5.833333	842.013358	5.777778	16.055556	1.000000	0.000000	0.000000
2	2685.889615	3.884615	710.264045	3.884615	10.230769	0.000000	1.000000	0.000000
3	6367.055000	8.722222	736.880743	8.222222	23.166667	0.111111	0.222222	0.000000
4	2101.315833	4.041667	537.536687	3.958333	9.000000	1.000000	0.000000	0.000000
5	5545.575909	6.954545	817.059878	6.590909	19.454545	0.000000	0.000000	1.000000
6	3223.288889	4.944444	658.735433	4.833333	12.777778	0.000000	0.000000	0.000000
7	2295.272000	2.400000	960.933556	2.333333	6.466667	0.266667	0.000000	0.000000
8	3141.587241	4.620690	694.194144	4.517241	11.206897	0.000000	0.000000	1.000000
9	3863.757857	7.214286	542.767724	7.214286	15.428571	0.000000	1.000000	0.000000

In [ ]: