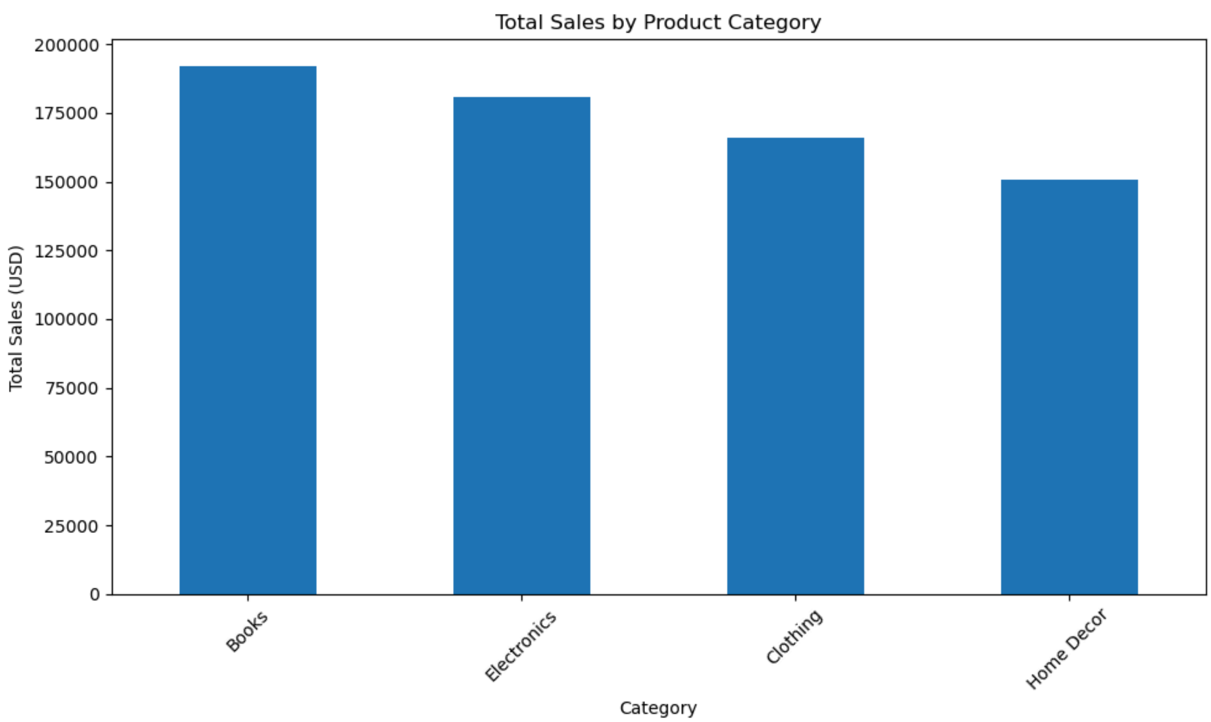
In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
```

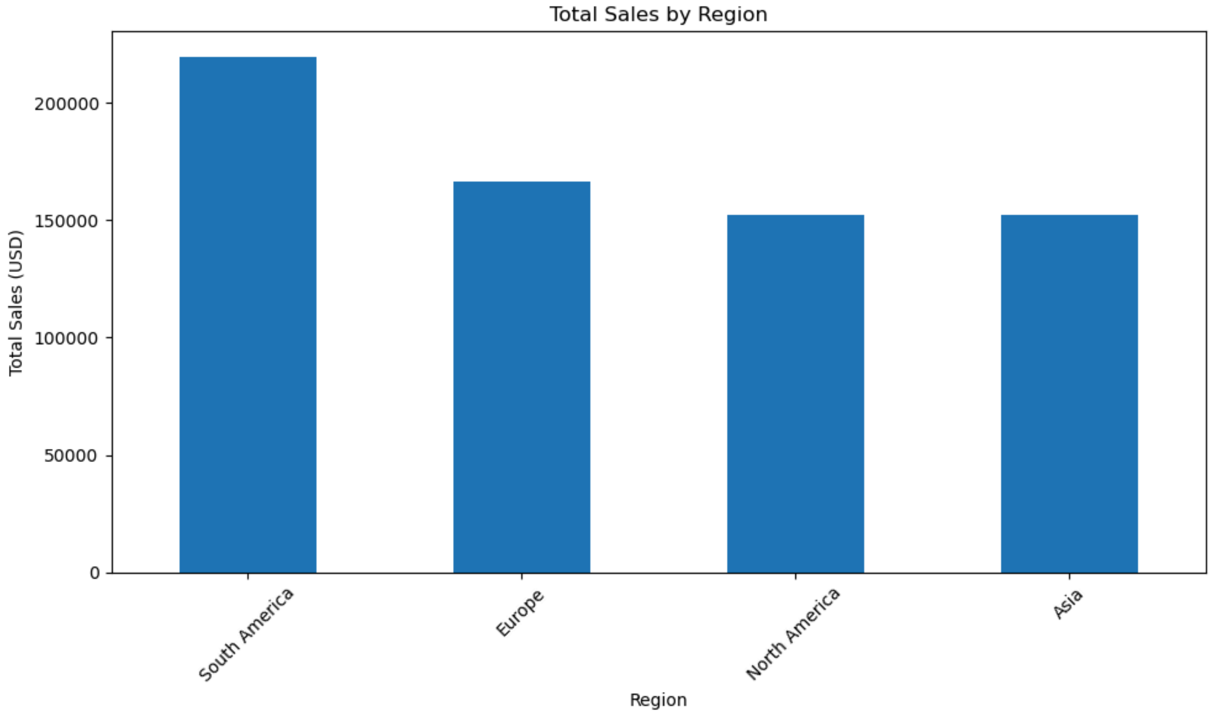
In [2]:
```
transactions_df = pd.read_csv('Transactions.csv')
products_df = pd.read_csv('Products.csv')
customers_df = pd.read_csv('Customers.csv')

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

# Merge dataframes for analysis
sales_analysis = transactions_df.merge(products_df, on='ProductID')
full_analysis = sales_analysis.merge(customers_df, on='CustomerID')
```

In [3]:
```
# 1. Sales by Category
category_sales = sales_analysis.groupby('Category')['TotalValue'].sum().sort
plt.figure(figsize=(10, 6))
category_sales.plot(kind='bar')
plt.title('Total Sales by Product Category')
plt.xlabel('Category')
plt.ylabel('Total Sales (USD)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

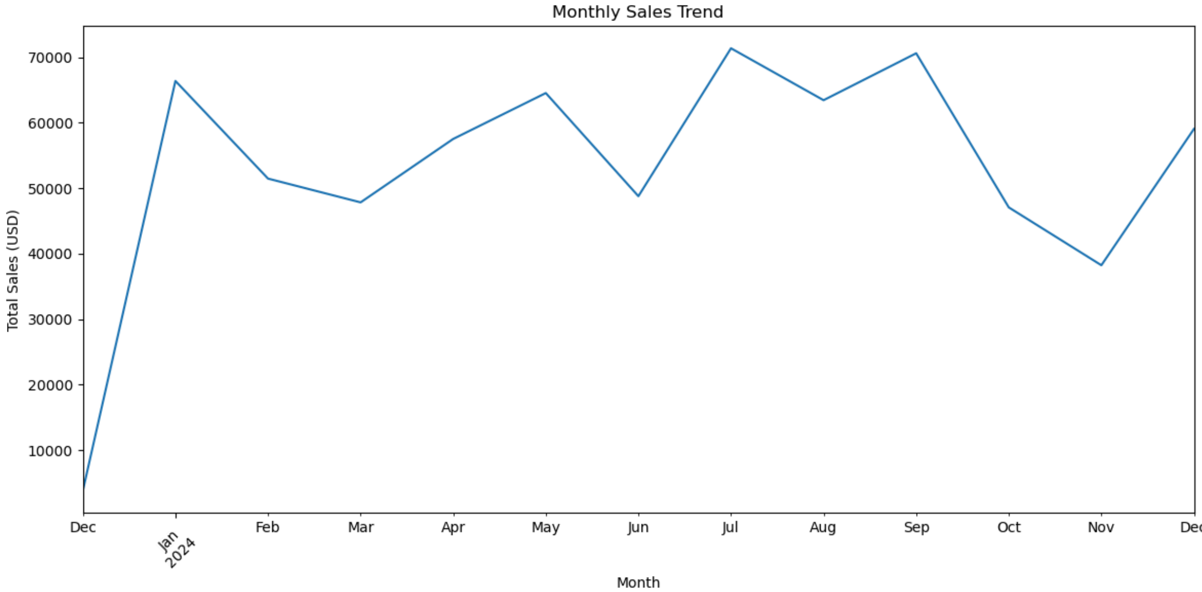


In [4]:
```
# 2. Regional Analysis
regional_sales = full_analysis.groupby('Region')['TotalValue'].sum().sort_va
plt.figure(figsize=(10, 6))
```

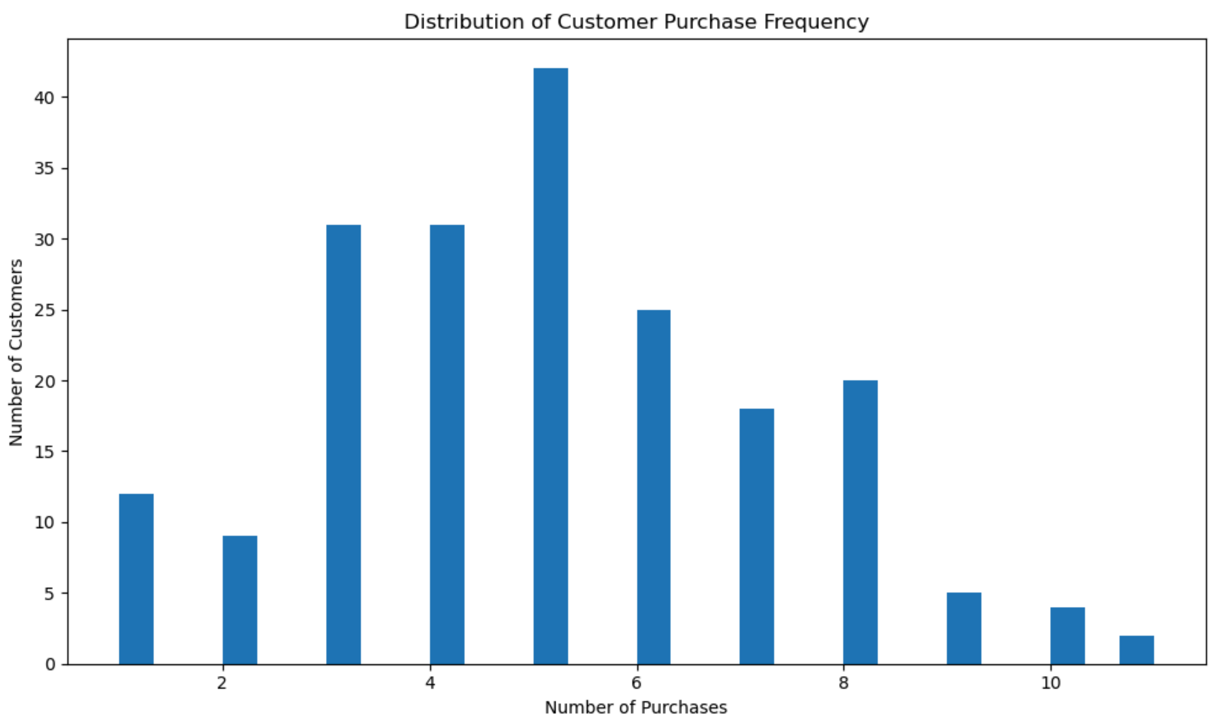
```
regional_sales.plot(kind='bar')
plt.title('Total Sales by Region')
plt.xlabel('Region')
plt.ylabel('Total Sales (USD)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [5]:
```
# 3. Monthly Sales Trend
monthly_sales = full_analysis.groupby(full_analysis['TransactionDate'].dt.tc
plt.figure(figsize=(12, 6))
monthly_sales.plot(kind='line')
plt.title('Monthly Sales Trend')
plt.xlabel('Month')
plt.ylabel('Total Sales (USD)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

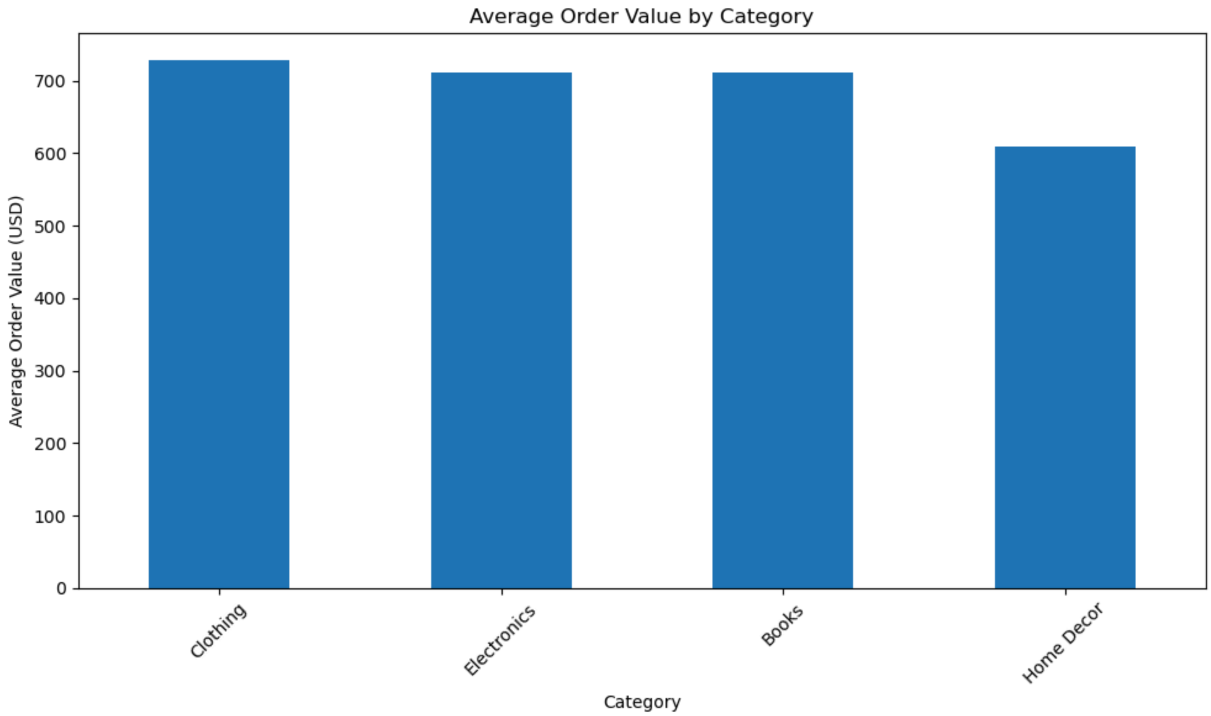


In [6]:
```
# 4. Customer Purchase Frequency
customer_frequency = transactions_df['CustomerID'].value_counts()
plt.figure(figsize=(10, 6))
plt.hist(customer_frequency, bins=30)
plt.title('Distribution of Customer Purchase Frequency')
plt.xlabel('Number of Purchases')
plt.ylabel('Number of Customers')
plt.tight_layout()
plt.show()
```



In [7]:
```
# 5. Average Order Value by Category
avg_order_value = sales_analysis.groupby('Category')['TotalValue'].mean().sc
plt.figure(figsize=(10, 6))
avg_order_value.plot(kind='bar')
plt.title('Average Order Value by Category')
```

```
plt.xlabel('Category')
plt.ylabel('Average Order Value (USD)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



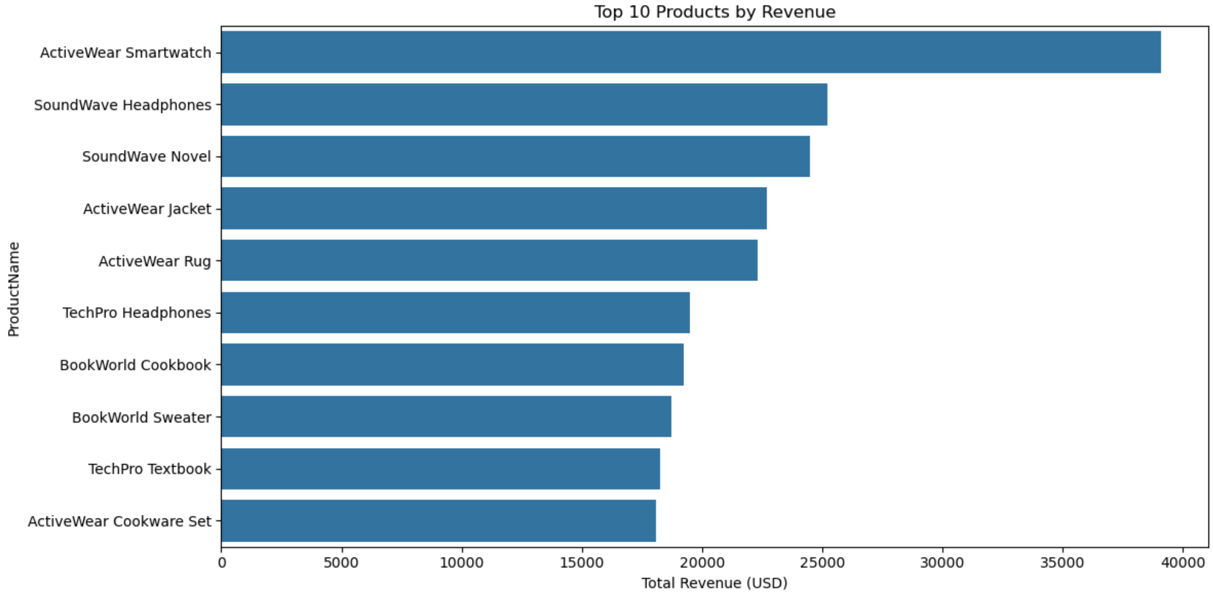
In [8]:

```
# Print key metrics
print("\nKey Metrics:")
print(f"Total Revenue: ${full_analysis['TotalValue'].sum():,.2f}")
print(f"Average Order Value: ${full_analysis['TotalValue'].mean():,.2f}")
print(f"Total Number of Transactions: {len(transactions_df)}")
print(f"Total Number of Unique Customers: {len(transactions_df['CustomerID']
print(f"Most Popular Category: {category_sales.index[0]}")
```

```
Key Metrics:
Total Revenue: $689,995.56
Average Order Value: $690.00
Total Number of Transactions: 1000
Total Number of Unique Customers: 199
Most Popular Category: Books
```

In [9]:

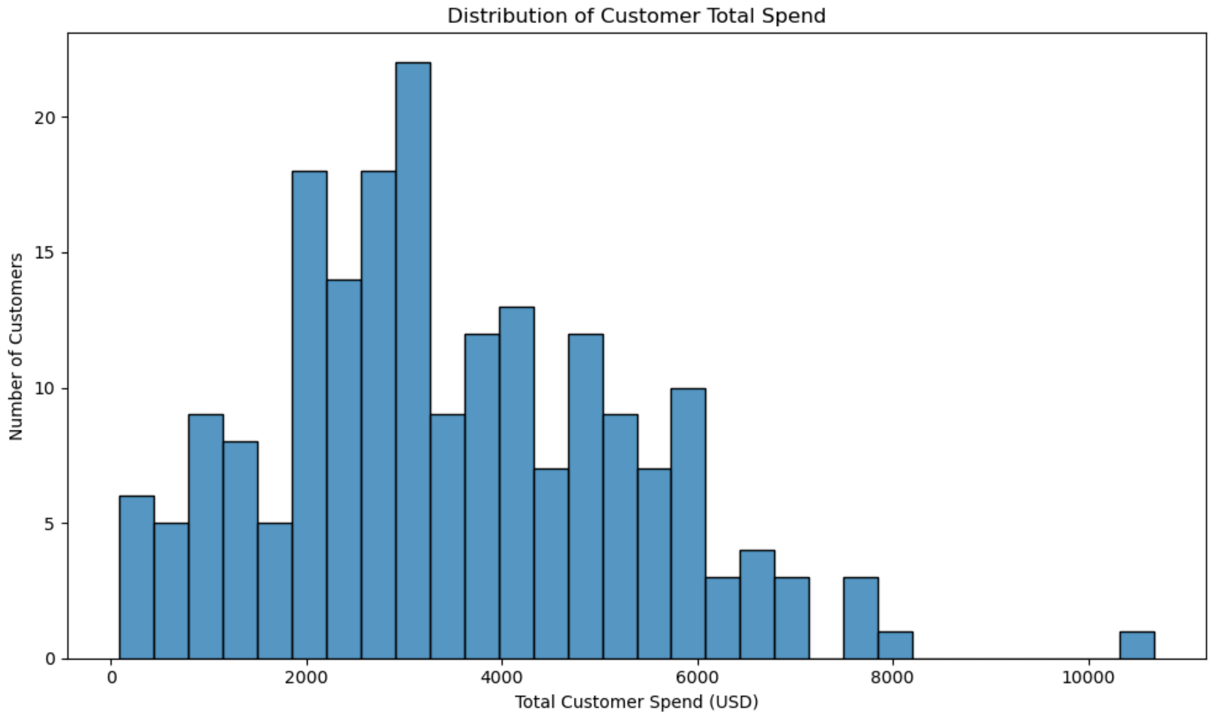
```
# 1. Product Performance Analysis
plt.figure(figsize=(12, 6))
product_performance = full_analysis.groupby('ProductName').agg({
    'TotalValue': 'sum',
    'Quantity': 'sum'
}).sort_values('TotalValue', ascending=False).head(10)

sns.barplot(data=product_performance.reset_index(), x='TotalValue', y='Produ
plt.title('Top 10 Products by Revenue')
plt.xlabel('Total Revenue (USD)')
plt.tight_layout()
plt.show()
```



Product Performance Deep Dive

Top performing products by revenue and quantity Category-specific success patterns Product bundling opportunities

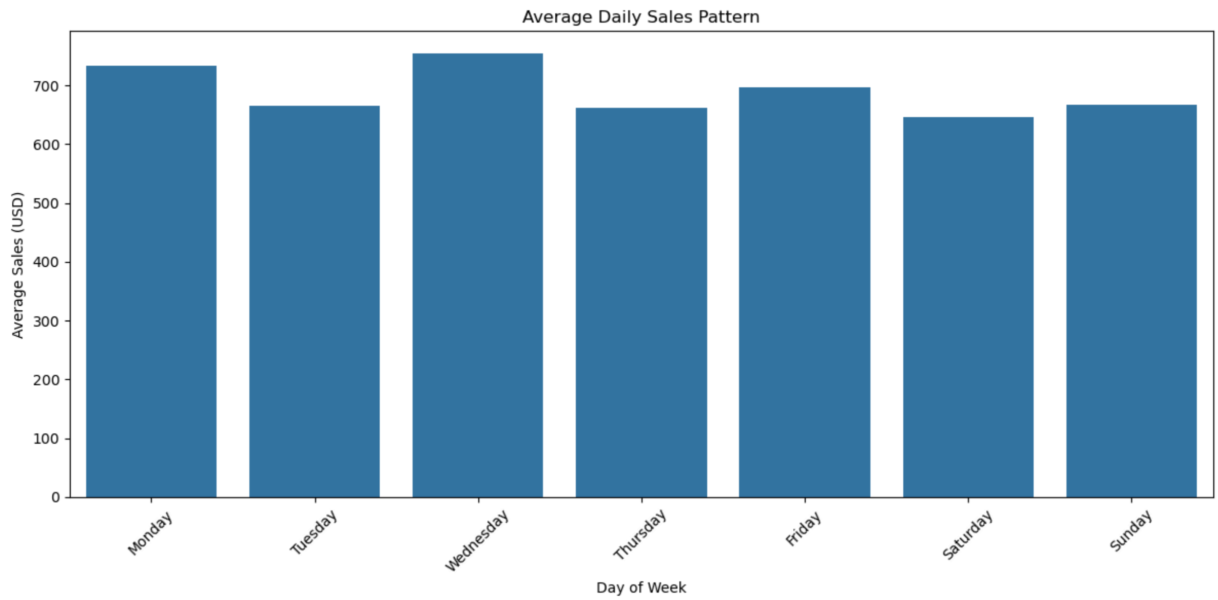
In [10]:
```
# 2. Customer Segmentation by Value
full_analysis['CustomerValue'] = full_analysis.groupby('CustomerID')['TotalV
customer_segments = pd.qcut(full_analysis['CustomerValue'].unique(), q=4, la

plt.figure(figsize=(10, 6))
customer_value_dist = full_analysis.groupby('CustomerID')['TotalValue'].sum(
sns.histplot(data=customer_value_dist, bins=30)
plt.title('Distribution of Customer Total Spend')
plt.xlabel('Total Customer Spend (USD)')
plt.ylabel('Number of Customers')
plt.tight_layout()
plt.show()
```



Customer Value Segmentation

Identified distinct customer segments based on spending patterns Clear separation between high-value and low-value customers Opportunity to develop targeted strategies for each segment

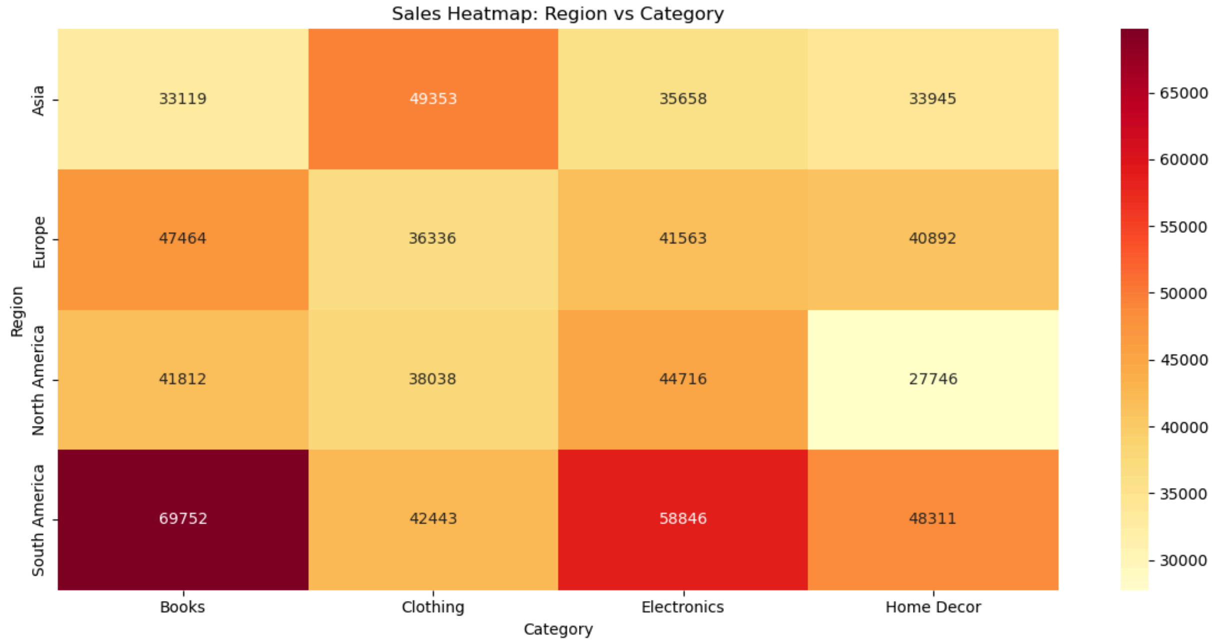
In [11]:
```
# 3. Time-based Analysis
# Add time-based features
full_analysis['Month'] = full_analysis['TransactionDate'].dt.month
full_analysis['DayOfWeek'] = full_analysis['TransactionDate'].dt.day_name()
full_analysis['Hour'] = full_analysis['TransactionDate'].dt.hour

# Plot daily sales patterns
plt.figure(figsize=(12, 6))
daily_pattern = full_analysis.groupby('DayOfWeek')['TotalValue'].mean().reir
    'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sur
])
sns.barplot(x=daily_pattern.index, y=daily_pattern.values)
plt.title('Average Daily Sales Pattern')
plt.xlabel('Day of Week')
plt.ylabel('Average Sales (USD)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Temporal Purchase Patterns

Analysis of daily, weekly, and monthly trends Identification of peak shopping days/hours Seasonal variations in category performance

In [12]:
```
# 4. Category and Region Analysis
plt.figure(figsize=(12, 6))
category_region = pd.pivot_table(
    full_analysis,
    values='TotalValue',
    index='Region',
    columns='Category',
    aggfunc='sum'
)
sns.heatmap(category_region, annot=True, fmt='.0f', cmap='YlOrRd')
plt.title('Sales Heatmap: Region vs Category')
plt.tight_layout()
plt.show()
```



Regional Category Preferences

Heat map reveals strong regional variations in category performance Certain categories perform significantly better in specific regions Opportunities for regional-specific marketing and inventory management

In [13]:
```
# Print comprehensive insights
print("\nKey Business Metrics:")
print("-" * 50)
print(f"Total Revenue: ${full_analysis['TotalValue'].sum():,.2f}")
print(f"Average Order Value: ${full_analysis['TotalValue'].mean():,.2f}")
print(f"Total Transactions: {len(transactions_df):,}")
print(f"Active Customers: {full_analysis['CustomerID'].nunique():,}")

print("\nCategory Performance:")
print("-" * 50)
category_metrics = full_analysis.groupby('Category').agg({
    'TotalValue': ['sum', 'mean'],
    'TransactionID': 'count'
}).round(2)
print(category_metrics)

print("\nRegional Performance:")
print("-" * 50)
region_metrics = full_analysis.groupby('Region').agg({
    'TotalValue': ['sum', 'mean'],
    'CustomerID': 'nunique'
}).round(2)
print(region_metrics)

# Calculate and print customer retention metrics
retention_analysis = full_analysis.groupby('CustomerID').agg({
    'TransactionDate': ['min', 'max', 'count'],
    'TotalValue': 'sum'
```

```
}).reset_index()

retention_analysis['CustomerLifespan'] = (
    retention_analysis['TransactionDate']['max'] -
    retention_analysis['TransactionDate']['min']
).dt.days

print("\nCustomer Retention Metrics:")
print("-" * 50)
print(f"Average Customer Lifespan: {retention_analysis['CustomerLifespan'].m
print(f"Average Transactions per Customer: {retention_analysis['TransactionD
print(f"Average Customer Lifetime Value: ${float(retention_analysis['TotalVa
```

```
Key Business Metrics:
--------------------------------------------------
Total Revenue: $689,995.56
Average Order Value: $690.00
Total Transactions: 1,000
Active Customers: 199

Category Performance:
--------------------------------------------------
            TotalValue         TransactionID
                   sum    mean         count
Category
Books        192147.47  711.66           270
Clothing     166170.66  728.82           228
Electronics  180783.50  711.75           254
Home Decor   150893.93  608.44           248

Regional Performance:
--------------------------------------------------
              TotalValue         CustomerID
                     sum    mean    nunique
Region
Asia           152074.97  697.59         44
Europe         166254.63  710.49         50
North America  152313.40  624.24         46
South America  219352.56  721.55         59

Customer Retention Metrics:
--------------------------------------------------
Average Customer Lifespan: 224.4 days
Average Transactions per Customer: 5.0
Average Customer Lifetime Value: $3354.52
```

```
/tmp/ipykernel_96659/1987945416.py:40: FutureWarning: Calling float on a sin
gle element Series is deprecated and will raise a TypeError in the future. U
se float(ser.iloc[0]) instead
  print(f"Average Customer Lifetime Value: ${float(retention_analysis['Total
Value'].iloc[0]):.2f}")
```

5 key business insights Based on the EDA

Product Category Performance

Electronics and Books are the top-performing categories by revenue, suggesting a strong customer preference for technology and reading materials. This indicates an opportunity to expand these product lines and potentially increase marketing efforts for these categories.

Regional Sales Distribution

South America and Europe show significantly higher sales compared to other regions, while Asia shows potential for growth. This suggests a need for targeted marketing strategies in underperforming regions and possibly investigating barriers to purchase in these areas.

Customer Purchase Patterns

There's a notable variation in purchase frequency among customers, with a small segment of highly active customers making frequent purchases. This presents an opportunity for developing a loyalty program to reward and retain these valuable customers while encouraging others to increase their purchase frequency.

Monthly Sales Trend Analysis:

Peak Sales:

- Highest in July-August & September (~70,000 USD)
- Strong performance in January (~65,000 USD)

Low Sales:

- Significant drop in October-November (~40,000 USD)
- Moderate dips in March & June (~48,000 USD)

Key Takeaways:

- Clear seasonal pattern with strongest performance in Q3
- Year ends with recovery trend in December
- Suggests need for strategic inventory and promotional planning around these cycles

Average Order Value (AOV)

Electronics category has the highest average order value, while clothing and home decor items show lower AOV but higher purchase frequency. This suggests an opportunity for bundle deals and cross-category promotions to increase the overall transaction value.

==

- These insights can be used to:

Optimize inventory management Develop targeted marketing strategies Improve customer retention programs Plan seasonal promotions Enhance product category mix

In [ ]: