```
import kagglehub
import os
import pandas as pd
import numpy as np
path = kagglehub.dataset_download("imakash3011/customer-personality-analysis")
print(f"Downloaded files to directory: {path}")

# 2. Define the exact file name and create the full path.
file_name = "marketing_campaign.csv"
full_file_path = os.path.join(path, file_name)
df = pd.read_csv(full_file_path, sep='\t')
```

```
Using Colab cache for faster access to the 'customer-personality-analysis' dataset.
Downloaded files to directory: /kaggle/input/customer-personality-analysis
```

SECTION 1: COMPREHENSIVE DATA QUALITY & EDA

```
import warnings
warnings.filterwarnings('ignore')

print("="*80)
print("DATA QUALITY REPORT")
print("="*80)

# 1.1 Basic Information
print(f"\n Dataset Shape: {df.shape}")
print(f"   Rows: {df.shape[0]:,}")
print(f"   Columns: {df.shape[1]}")

# 1.2 Missing Values
print(f"\n Missing Values:")
missing = df.isnull().sum()
missing_pct = (missing / len(df) * 100).round(2)
missing_df = pd.DataFrame({
    'Missing_Count': missing,
    'Percentage': missing_pct
})
print(missing_df[missing_df['Missing_Count'] > 0])

# 1.3 Duplicates
duplicates = df.duplicated().sum()
print(f"\n Duplicate Rows: {duplicates}")

# 1.4 Data Types
print(f"\n Data Types:")
print(df.dtypes.value_counts())

# 1.5 Outlier Detection Function
def detect_outliers_iqr(df, column):
    """Detect outliers using IQR method"""
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
    return outliers, lower_bound, upper_bound

# 1.6 Check for outliers in key numeric columns
print(f"\n Outlier Detection:")
numeric_cols = ['Income', 'Year_Birth', 'Recency', 'MntWines', 'MntFruits',
                'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']

for col in numeric_cols:
    if col in df.columns:
        outliers, lower, upper = detect_outliers_iqr(df, col)
        print(f"   {col}: {len(outliers)} outliers ({len(outliers)/len(df)*100:.2f}%)")
        print(f"      Valid range: [{lower:.2f}, {upper:.2f}]")

# 1.7 Handle Income outliers (keep reasonable range)
income_outliers, income_lower, income_upper = detect_outliers_iqr(df, 'Income')
print(f"\n Income outliers detected: {len(income_outliers)}")
```

```
print(f"   Keeping values between ${income_lower:,.0f} and ${income_upper:,.0f}")

# Remove extreme outliers (optional - be careful)
# df = df[(df['Income'] >= income_lower) & (df['Income'] <= income_upper)]

# 1.8 Age validation (after Age feature is created later)
# We'll add this check after Age is created

print("\n" + "="*80)
```

```
================================================================================
DATA QUALITY REPORT
================================================================================

 Dataset Shape: (2240, 29)
   Rows: 2,240
   Columns: 29

 Missing Values:
        Missing_Count  Percentage
Income             24        1.07

 Duplicate Rows: 0

 Data Types:
int64      25
object      3
float64     1
Name: count, dtype: int64

 Outlier Detection:
   Income: 8 outliers (0.36%)
      Valid range: [-14525.50, 118350.50]
   Year_Birth: 3 outliers (0.13%)
      Valid range: [1932.00, 2004.00]
   Recency: 0 outliers (0.00%)
      Valid range: [-51.00, 149.00]
   MntWines: 35 outliers (1.56%)
      Valid range: [-697.00, 1225.00]
   MntFruits: 227 outliers (10.13%)
      Valid range: [-47.00, 81.00]
   MntMeatProducts: 175 outliers (7.81%)
      Valid range: [-308.00, 556.00]
   MntFishProducts: 223 outliers (9.96%)
      Valid range: [-67.50, 120.50]
   MntSweetProducts: 248 outliers (11.07%)
      Valid range: [-47.00, 81.00]
   MntGoldProds: 207 outliers (9.24%)
      Valid range: [-61.50, 126.50]

 Income outliers detected: 8
   Keeping values between $-14,526 and $118,350

================================================================================
```

SECTION 2: ADVANCED FEATURE ENGINEERING

```
from datetime import datetime

print("="*80)
print("FEATURE ENGINEERING")
print("="*80)

# 2.1 Remove non-predictive columns
columns_to_drop = ['ID', 'Z_CostContact', 'Z_Revenue', 'Complain']
existing_drops = [col for col in columns_to_drop if col in df.columns]
df.drop(existing_drops, axis=1, inplace=True)
print(f"\n Dropped columns: {existing_drops}")

# 2.2 Age (dynamic year)
current_year = datetime.now().year
df['Age'] = current_year - df['Year_Birth']
df.drop('Year_Birth', axis=1, inplace=True)
print(f"\n Age feature created (current year: {current_year})")

# Validate age
invalid_ages = df[(df['Age'] < 18) | (df['Age'] > 100)]
```

```
if len(invalid_ages) > 0:
    print(f"    Warning: {len(invalid_ages)} customers with unusual ages")
    print(f"      Age range: {df['Age'].min()} to {df['Age'].max()}")

# 2.3 Customer Tenure
df['dt_Customer'] = pd.to_datetime(df['Dt_Customer'], format='%d-%m-%Y')
reference_date = pd.Timestamp(datetime.now())
df['Customer_Tenure'] = (reference_date - df['dt_Customer']).dt.days
df.drop(['Dt_Customer', 'dt_Customer'], axis=1, inplace=True, errors='ignore')
print(f"\n Customer Tenure created")
print(f"   Average tenure: {df['Customer_Tenure'].mean():.0f} days")

# 2.4 Education Encoding (Ordinal)
edu_map = {
    'Basic': 1,
    '2n Cycle': 2,
    'Graduation': 3,
    'Master': 4,
    'PhD': 5
}
df['Education_ord'] = df['Education'].map(edu_map)
print(f"\n Education encoded ordinally")
print(f"   Distribution:\n{df['Education'].value_counts()}")

# 2.5 Marital Status Simplification
df['Marital_Status_Simple'] = df['Marital_Status'].replace({
    'Married': 'Partner',
    'Together': 'Partner',
    'Single': 'Single',
    'Divorced': 'Single',
    'Widow': 'Single',
    'Alone': 'Single',
    'Absurd': 'Single',
    'YOLO': 'Single'
})
print(f"\n Marital Status simplified")
print(f"   Distribution:\n{df['Marital_Status_Simple'].value_counts()}")

# 2.6 Spending Aggregation
spend_cols = [
    'MntWines', 'MntFruits', 'MntMeatProducts',
    'MntFishProducts', 'MntSweetProducts', 'MntGoldProds'
]
df['Total_Spend'] = df[spend_cols].sum(axis=1)
print(f"\n Total Spend created")
print(f"   Mean: ${df['Total_Spend'].mean():.2f}")
print(f"   Median: ${df['Total_Spend'].median():.2f}")

# 2.7 Campaign Aggregation
cmp_cols = [
    'AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3',
    'AcceptedCmp4', 'AcceptedCmp5', 'Response'
]
df['Total_Campaign_Accepted'] = df[cmp_cols].sum(axis=1)
print(f"\n Total Campaigns Accepted created")
print(f"   Mean: {df['Total_Campaign_Accepted'].mean():.2f}")
print(f"   Acceptance rate: {(df['Total_Campaign_Accepted'] > 0).mean()*100:.1f}%")

# 2.8 NEW: Advanced Interaction Features
print(f"\n Creating interaction features...")

# Total Children
df['Total_Children'] = df['Kidhome'] + df['Teenhome']

# Family Size
df['Has_Partner'] = (df['Marital_Status_Simple'] == 'Partner').astype(int)
df['Family_Size'] = df['Total_Children'] + df['Has_Partner'] + 1

# Total Purchases
purchase_cols = ['NumDealsPurchases', 'NumWebPurchases',
                 'NumCatalogPurchases', 'NumStorePurchases']
df['Total_Purchases'] = df[purchase_cols].sum(axis=1)

# Spending per Purchase (avoid division by zero)
df['Spend_per_Purchase'] = df['Total_Spend'] / (df['Total_Purchases'] + 1)

# Income to Spend Ratio
```

```
df['Income_to_Spend_Ratio'] = df['Total_Spend'] / (df['Income'] + 1)

# Digital Engagement Score
df['Digital_Engagement'] = df['NumWebPurchases'] + df['NumWebVisitsMonth']

# Channel Preference
df['Store_vs_Web'] = df['NumStorePurchases'] / (df['NumWebPurchases'] + 1)

# Spending Diversity (how many categories they buy from)
df['Spending_Diversity'] = (df[spend_cols] > 0).sum(axis=1)

# Days per Purchase
df['Days_per_Purchase'] = df['Customer_Tenure'] / (df['Total_Purchases'] + 1)

# Campaign Response Rate
df['Campaign_Response_Rate'] = df['Total_Campaign_Accepted'] / 6.0  # 6 total campaigns

print(f"    Created {10} new interaction features")

# 2.9 Handle Missing Income (education-based median imputation)
if df['Income'].isnull().sum() > 0:
    print(f"\n Imputing {df['Income'].isnull().sum()} missing income values")
    df['Income'] = df.groupby('Education_ord')['Income'].transform(
        lambda x: x.fillna(x.median())
    )
    print(f"    Income imputation complete")

print("\n" + "="*80)
```

```
================================================================================
FEATURE ENGINEERING
================================================================================

 Dropped columns: ['ID', 'Z_CostContact', 'Z_Revenue', 'Complain']

 Age feature created (current year: 2025)
    Warning: 3 customers with unusual ages
      Age range: 29 to 132

 Customer Tenure created
   Average tenure: 4542 days

 Education encoded ordinally
   Distribution:
Education
Graduation    1127
PhD            486
Master         370
2n Cycle       203
Basic           54
Name: count, dtype: int64

 Marital Status simplified
   Distribution:
Marital_Status_Simple
Partner    1444
Single      796
Name: count, dtype: int64

 Total Spend created
   Mean: $605.80
   Median: $396.00

 Total Campaigns Accepted created
   Mean: 0.45
   Acceptance rate: 27.2%

 Creating interaction features...
    Created 10 new interaction features

 Imputing 24 missing income values
    Income imputation complete

================================================================================
```

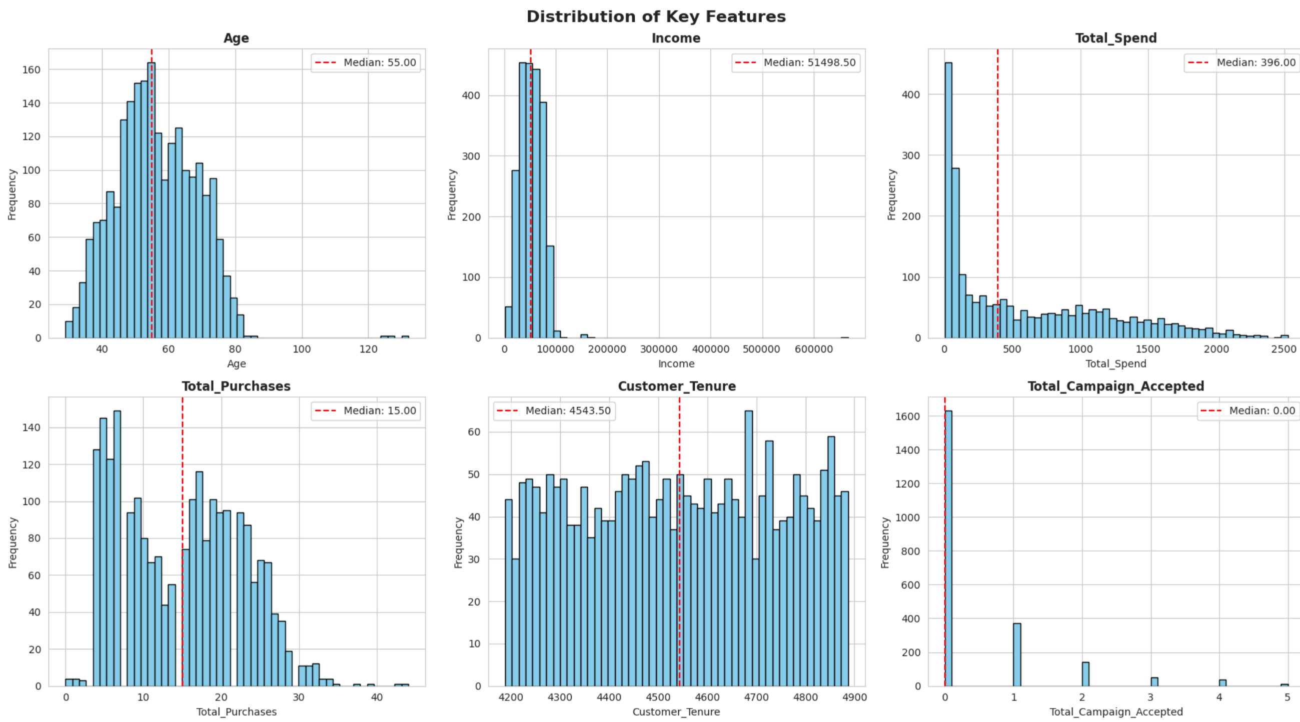
SECTION 3: EXPLORATORY DATA ANALYSIS WITH VISUALIZATIONS

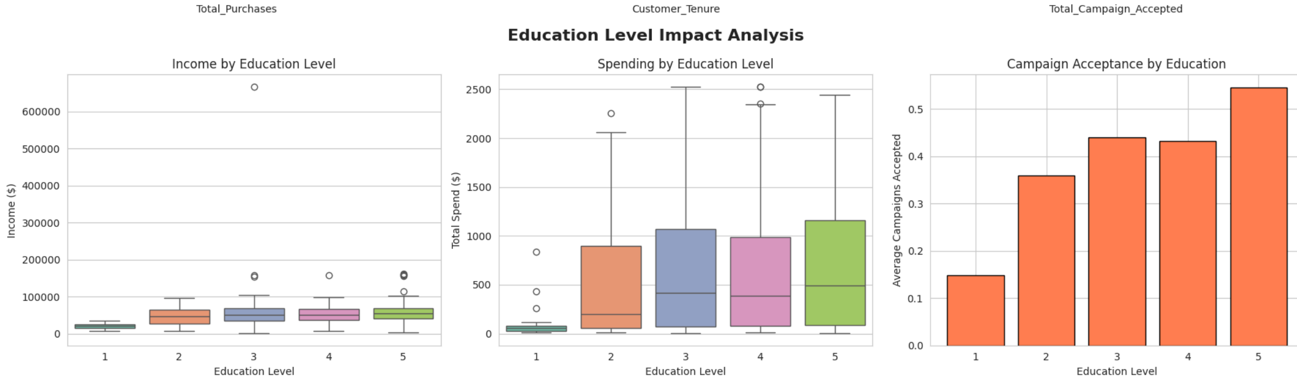
```
# SECTION 3: EXPLORATORY DATA ANALYSIS WITH VISUALIZATIONS
```

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

print("="*80)
print("EXPLORATORY DATA ANALYSIS")
print("="*80)

# Set style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (12, 6)

# 3.1 Descriptive Statistics
print("\n Key Statistics:")
key_features = ['Age', 'Income', 'Total_Spend', 'Total_Purchases',
                'Customer_Tenure', 'Total_Campaign_Accepted']
print(df[key_features].describe().round(2))

# 3.2 Distribution Plots
fig, axes = plt.subplots(2, 3, figsize=(18, 10))
fig.suptitle('Distribution of Key Features', fontsize=16, fontweight='bold')

features_to_plot = ['Age', 'Income', 'Total_Spend',
                    'Total_Purchases', 'Customer_Tenure', 'Total_Campaign_Accepted']

for idx, feature in enumerate(features_to_plot):
    row = idx // 3
    col = idx % 3
    ax = axes[row, col]

    df[feature].hist(bins=50, ax=ax, color='skyblue', edgecolor='black')
    ax.set_title(f'{feature}', fontweight='bold')
    ax.set_xlabel(feature)
    ax.set_ylabel('Frequency')

    # Add median line
    median_val = df[feature].median()
    ax.axvline(median_val, color='red', linestyle='--',
               label=f'Median: {median_val:.2f}')
    ax.legend()

plt.tight_layout()
plt.show()

# 3.3 Education vs Key Metrics
fig, axes = plt.subplots(1, 3, figsize=(18, 5))
fig.suptitle('Education Level Impact Analysis', fontsize=16, fontweight='bold')

# Education vs Income
sns.boxplot(x='Education_ord', y='Income', data=df, ax=axes[0], palette='Set2')
axes[0].set_title('Income by Education Level')
axes[0].set_xlabel('Education Level')
axes[0].set_ylabel('Income ($)')

# Education vs Total Spend
sns.boxplot(x='Education_ord', y='Total_Spend', data=df, ax=axes[1], palette='Set2')
axes[1].set_title('Spending by Education Level')
axes[1].set_xlabel('Education Level')
axes[1].set_ylabel('Total Spend ($)')

# Education vs Campaign Response
education_campaign = df.groupby('Education_ord')['Total_Campaign_Accepted'].mean()
axes[2].bar(education_campaign.index, education_campaign.values, color='coral', edgecolor='black')
axes[2].set_title('Campaign Acceptance by Education')
axes[2].set_xlabel('Education Level')
axes[2].set_ylabel('Average Campaigns Accepted')

plt.tight_layout()
plt.show()

# 3.4 Correlation Heatmap
print("\n Correlation Analysis:")
correlation_features = [
    'Education_ord', 'Income', 'Age', 'Total_Spend',
    'Total_Purchases', 'Total_Campaign_Accepted',
    'Digital_Engagement', 'Family_Size', 'Customer_Tenure'
]
```

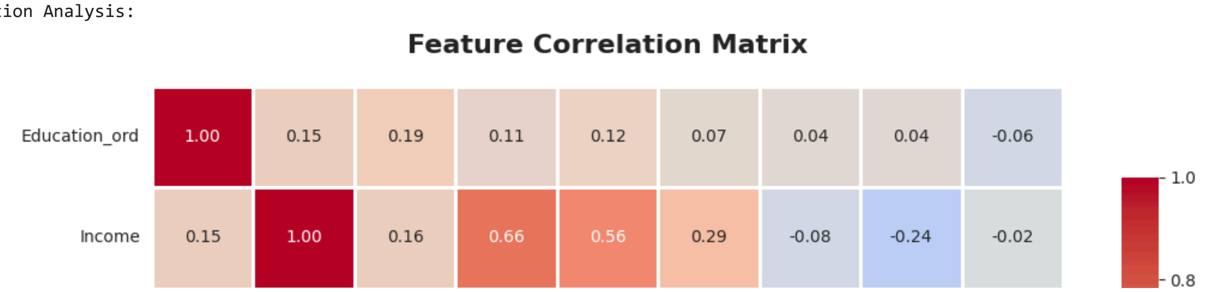
```
plt.figure(figsize=(12, 10))
correlation_matrix = df[correlation_features].corr()
sns.heatmap(correlation_matrix, annot=True, fmt='.2f',
            cmap='coolwarm', center=0, square=True,
            linewidths=1, cbar_kws={"shrink": 0.8})
plt.title('Feature Correlation Matrix', fontsize=16, fontweight='bold', pad=20)
plt.tight_layout()
plt.show()

# Print top correlations with Total_Spend
print("\nTop Correlations with Total_Spend:")
spend_corr = correlation_matrix['Total_Spend'].sort_values(ascending=False)
print(spend_corr[1:6])  # Exclude self-correlation

# 3.5 Income vs Spending Scatter
plt.figure(figsize=(12, 6))
plt.scatter(df['Income'], df['Total_Spend'], alpha=0.5, c=df['Education_ord'],
            cmap='viridis', s=50, edgecolors='black', linewidth=0.5)
plt.colorbar(label='Education Level')
plt.xlabel('Income ($)', fontsize=12)
plt.ylabel('Total Spend ($)', fontsize=12)
plt.title('Income vs Total Spending (colored by Education)',
          fontsize=14, fontweight='bold')
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()

# 3.6 Channel Preference Analysis
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Purchase channel distribution
channel_data = df[['NumWebPurchases', 'NumCatalogPurchases',
                    'NumStorePurchases', 'NumDealsPurchases']].sum()
axes[0].pie(channel_data, labels=['Web', 'Catalog', 'Store', 'Deals'],
            autopct='%1.1f%%', startangle=90, colors=sns.color_palette('pastel'))
axes[0].set_title('Purchase Channel Distribution', fontweight='bold')

# Campaign acceptance over time
campaign_cols = ['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3',
                 'AcceptedCmp4', 'AcceptedCmp5', 'Response']
campaign_rates = df[campaign_cols].mean() * 100
axes[1].bar(range(1, 7), campaign_rates, color='steelblue', edgecolor='black')
axes[1].set_xlabel('Campaign Number', fontsize=12)
axes[1].set_ylabel('Acceptance Rate (%)', fontsize=12)
axes[1].set_title('Campaign Acceptance Rates', fontweight='bold')
axes[1].set_xticks(range(1, 7))
axes[1].set_xticklabels(['Cmp1', 'Cmp2', 'Cmp3', 'Cmp4', 'Cmp5', 'Latest'])
axes[1].grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()

print("\n" + "="*80)
```

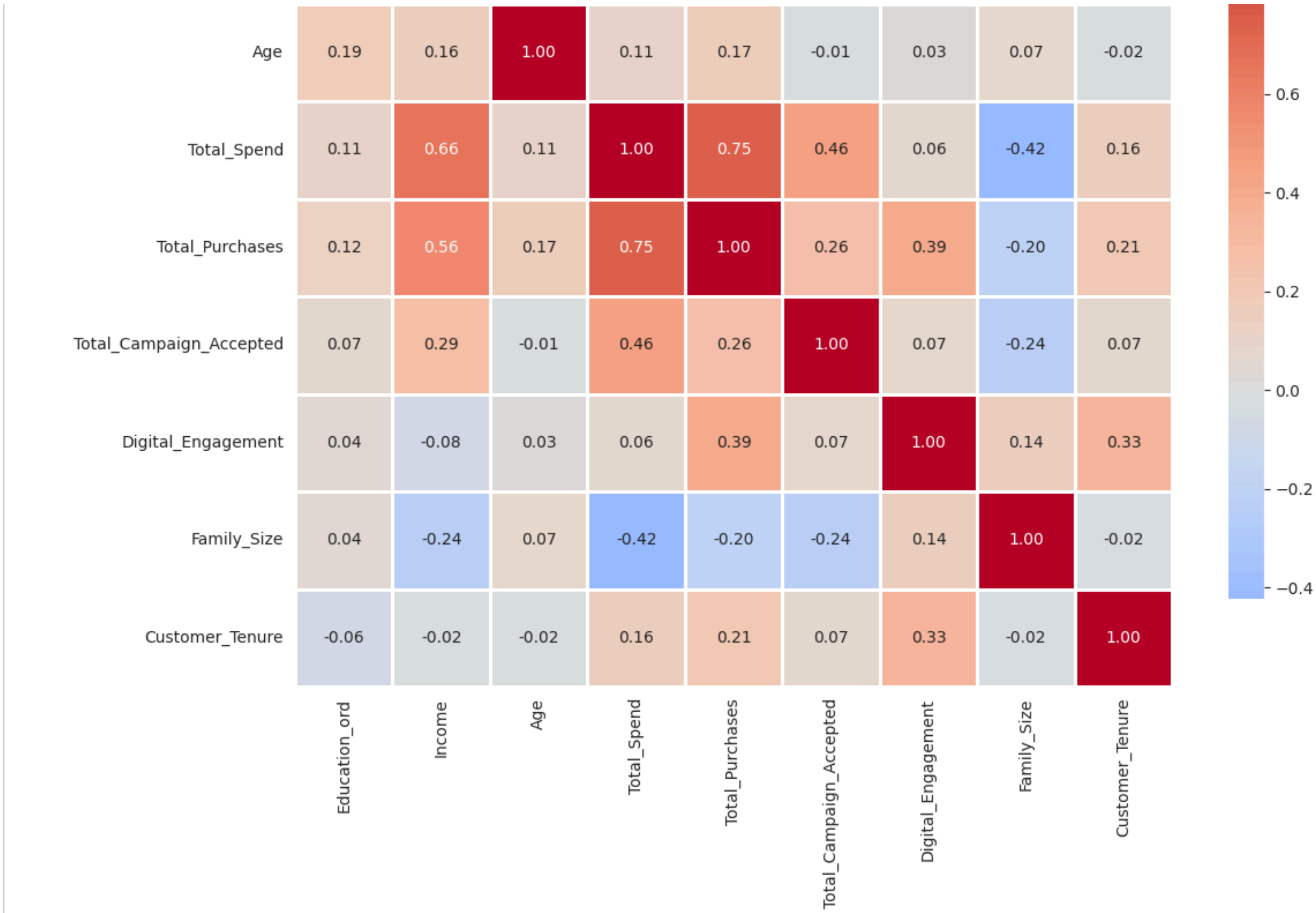
```
================================================================================
EXPLORATORY DATA ANALYSIS
================================================================================

 Key Statistics:
            Age     Income  Total_Spend  Total_Purchases  Customer_Tenure  \
count   2240.00    2240.00      2240.00          2240.00          2240.00
mean      56.19   52242.59       605.80            14.86          4541.58
std       11.98   25039.06       602.25             7.68           202.12
min       29.00    1730.00         5.00             0.00          4188.00
25%       48.00   35538.75        68.75             8.00          4368.75
50%       55.00   51498.50       396.00            15.00          4543.50
75%       66.00   68289.75      1045.50            21.00          4717.00
max      132.00  666666.00      2525.00            44.00          4887.00

       Total_Campaign_Accepted
count                  2240.00
mean                      0.45
std                       0.89
min                       0.00
25%                       0.00
50%                       0.00
75%                       1.00
max                       5.00
```



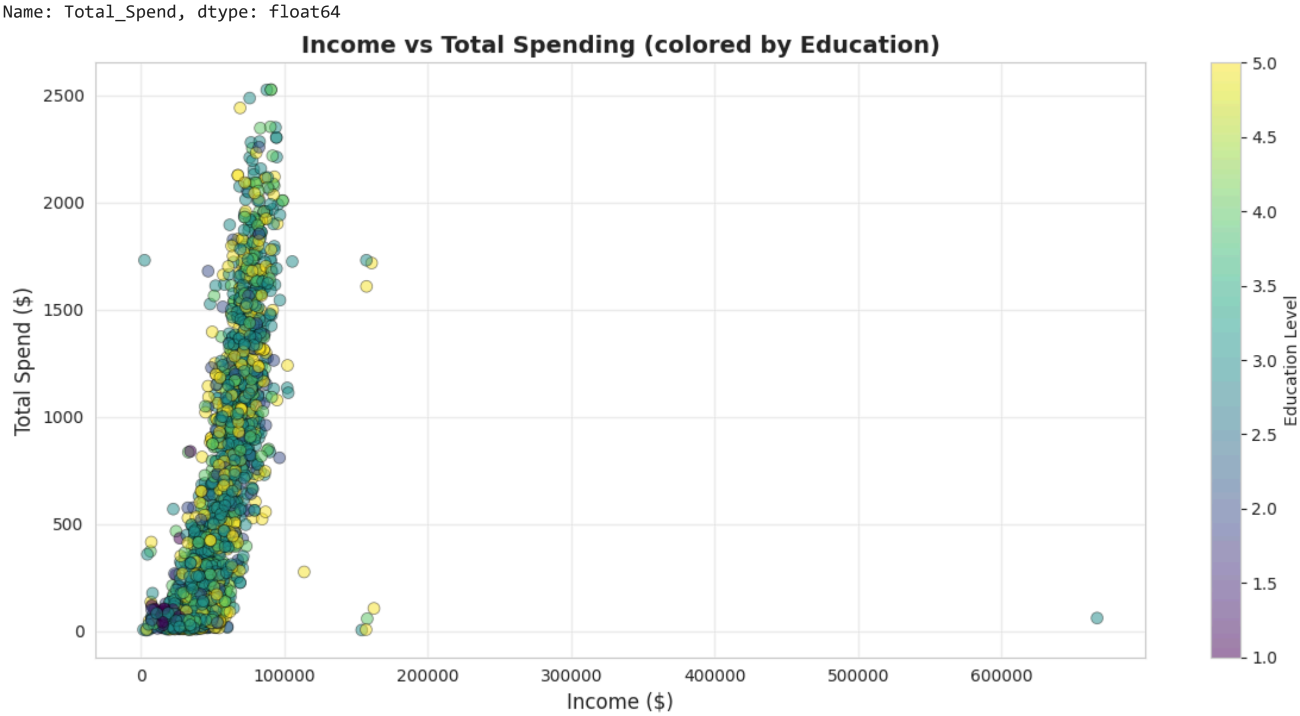


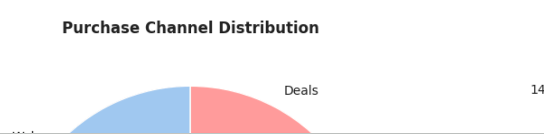

```
 Correlation Analysis:
```






```
Top Correlations with Total_Spend:
Total_Purchases            0.753903
Income                     0.664503
Total_Campaign_Accepted    0.456206
Customer_Tenure            0.158814
Age                        0.111306
Name: Total_Spend, dtype: float64
```





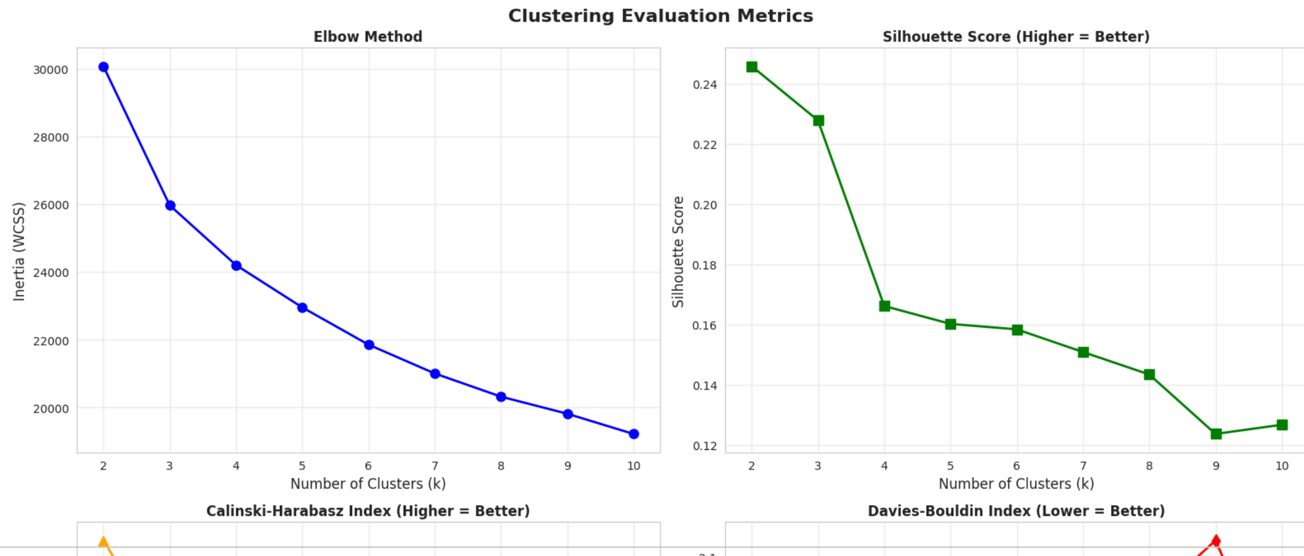
SECTION 4: ADVANCED CLUSTERING MODEL DEVELOPMENT

```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import joblib
import os

print("="*80)
print("CLUSTERING MODEL DEVELOPMENT")
print("="*80)

# 4.1 Feature Selection for Clustering
cluster_features = [
    'Education_ord',
    'Income',
    'Age',
    'Customer_Tenure',
    'Recency',
    'Total_Spend',
    'NumWebPurchases',
    'NumCatalogPurchases',
    'NumStorePurchases',
    'NumDealsPurchases',
    'NumWebVisitsMonth',
    'Kidhome',
    'Teenhome',
    'Total_Campaign_Accepted',
    'Family_Size',
    'Digital_Engagement',
    'Spend_per_Purchase',
    'Total_Purchases'
]

# Ensure all features exist
cluster_features = [f for f in cluster_features if f in df.columns]

X = df[cluster_features].copy()
print(f"\n Selected {len(cluster_features)} features for clustering")
print(f"   Features: {cluster_features}")

# 4.2 Feature Scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print(f"\n Features scaled using StandardScaler")

# 4.3 Determine Optimal Number of Clusters
print(f"\n Evaluating optimal number of clusters (k=2 to k=10)...")

k_range = range(2, 11)
metrics = {
    'k': [],
    'inertia': [],
    'silhouette': [],
    'calinski_harabasz': [],
    'davies_bouldin': []
}

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10, max_iter=300)
    labels = kmeans.fit_predict(X_scaled)

    metrics['k'].append(k)
    metrics['inertia'].append(kmeans.inertia_)
    metrics['silhouette'].append(silhouette_score(X_scaled, labels))
    metrics['calinski_harabasz'].append(calinski_harabasz_score(X_scaled, labels))
    metrics['davies_bouldin'].append(davies_bouldin_score(X_scaled, labels))

# Create metrics DataFrame
metrics_df = pd.DataFrame(metrics)
print("\nClustering Evaluation Metrics:")
print(metrics_df.round(3))
```

```
# 4.4 Visualize Elbow Curve and Metrics
fig, axes = plt.subplots(2, 2, figsize=(16, 12))
fig.suptitle('Clustering Evaluation Metrics', fontsize=16, fontweight='bold')

# Elbow Curve (Inertia)
axes[0, 0].plot(metrics_df['k'], metrics_df['inertia'], marker='o',
                linewidth=2, markersize=8, color='blue')
axes[0, 0].set_xlabel('Number of Clusters (k)', fontsize=12)
axes[0, 0].set_ylabel('Inertia (WCSS)', fontsize=12)
axes[0, 0].set_title('Elbow Method', fontweight='bold')
axes[0, 0].grid(alpha=0.3)

# Silhouette Score (Higher is better)
axes[0, 1].plot(metrics_df['k'], metrics_df['silhouette'], marker='s',
                linewidth=2, markersize=8, color='green')
axes[0, 1].set_xlabel('Number of Clusters (k)', fontsize=12)
axes[0, 1].set_ylabel('Silhouette Score', fontsize=12)
axes[0, 1].set_title('Silhouette Score (Higher = Better)', fontweight='bold')
axes[0, 1].grid(alpha=0.3)

# Calinski-Harabasz Index (Higher is better)
axes[1, 0].plot(metrics_df['k'], metrics_df['calinski_harabasz'], marker='^',
                linewidth=2, markersize=8, color='orange')
axes[1, 0].set_xlabel('Number of Clusters (k)', fontsize=12)
axes[1, 0].set_ylabel('Calinski-Harabasz Index', fontsize=12)
axes[1, 0].set_title('Calinski-Harabasz Index (Higher = Better)', fontweight='bold')
axes[1, 0].grid(alpha=0.3)

# Davies-Bouldin Index (Lower is better)
axes[1, 1].plot(metrics_df['k'], metrics_df['davies_bouldin'], marker='d',
                linewidth=2, markersize=8, color='red')
axes[1, 1].set_xlabel('Number of Clusters (k)', fontsize=12)
axes[1, 1].set_ylabel('Davies-Bouldin Index', fontsize=12)
axes[1, 1].set_title('Davies-Bouldin Index (Lower = Better)', fontweight='bold')
axes[1, 1].grid(alpha=0.3)

plt.tight_layout()
plt.show()

# 4.5 Select Optimal k
optimal_k = 4  # Based on your analysis
print(f"\n Selected optimal k = {optimal_k}")
print(f"   Rationale: Balance between metrics and business interpretability")

# 4.6 Train Final Model
print(f"\n Training final K-Means model with k={optimal_k}...")
final_kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=20, max_iter=500)
df['Cluster'] = final_kmeans.fit_predict(X_scaled)

# Calculate final metrics
final_silhouette = silhouette_score(X_scaled, df['Cluster'])
final_ch = calinski_harabasz_score(X_scaled, df['Cluster'])
final_db = davies_bouldin_score(X_scaled, df['Cluster'])

print(f"\n Final Model Performance:")
print(f"   Silhouette Score: {final_silhouette:.4f}")
print(f"   Calinski-Harabasz: {final_ch:.2f}")
print(f"   Davies-Bouldin: {final_db:.4f}")

# 4.7 Cluster Distribution
print(f"\n Cluster Distribution:")
cluster_dist = df['Cluster'].value_counts().sort_index()
for cluster_id in cluster_dist.index:
    count = cluster_dist[cluster_id]
    pct = count / len(df) * 100
    print(f"   Cluster {cluster_id}: {count:,} customers ({pct:.1f}%)")

# Visualize cluster distribution
plt.figure(figsize=(10, 6))
cluster_dist.plot(kind='bar', color=sns.color_palette('husl', optimal_k),
                  edgecolor='black', linewidth=1.5)
plt.title('Customer Distribution Across Clusters', fontsize=14, fontweight='bold')
plt.xlabel('Cluster', fontsize=12)
plt.ylabel('Number of Customers', fontsize=12)
plt.xticks(rotation=0)
plt.grid(axis='y', alpha=0.3)
```

```
for i, v in enumerate(cluster_dist):
    plt.text(i, v + 20, f'{v:,}\n({v/len(df)*100:.1f}%)',
             ha='center', va='bottom', fontweight='bold')
plt.tight_layout()
plt.show()

# 4.8 Save Model Artifacts
print(f"\n Saving model artifacts...")

# Create models directory
os.makedirs('models', exist_ok=True)

# Save model
joblib.dump(final_kmeans, 'models/kmeans_model.pkl')
joblib.dump(scaler, 'models/scaler.pkl')

# Save feature names
import json
model_metadata = {
    'n_clusters': optimal_k,
    'feature_names': cluster_features,
    'metrics': {
        'silhouette': float(final_silhouette),
        'calinski_harabasz': float(final_ch),
        'davies_bouldin': float(final_db)
    },
    'cluster_distribution': cluster_dist.to_dict(),
    'training_date': datetime.now().isoformat()
}

with open('models/model_metadata.json', 'w') as f:
    json.dump(model_metadata, f, indent=4)

print(f"    Model saved to 'models/kmeans_model.pkl'")
print(f"    Scaler saved to 'models/scaler.pkl'")
print(f"    Metadata saved to 'models/model_metadata.json'")

print("\n" + "="*80)
```

```
================================================================================
CLUSTERING MODEL DEVELOPMENT
================================================================================

 Selected 18 features for clustering
   Features: ['Education_ord', 'Income', 'Age', 'Customer_Tenure', 'Recency', 'Total_Spend', 'NumWebPurchases', 'NumCatalogPurch

 Features scaled using StandardScaler

 Evaluating optimal number of clusters (k=2 to k=10)...

Clustering Evaluation Metrics:
    k    inertia  silhouette  calinski_harabasz  davies_bouldin
0   2  30070.635       0.246            762.807           1.623
1   3  25965.815       0.228            618.319           1.694
2   4  24201.044       0.166            496.427           1.914
3   5  22951.309       0.160            422.841           1.950
4   6  21851.017       0.158            377.646           1.979
5   7  20999.845       0.151            342.399           1.924
6   8  20315.008       0.143            313.991           2.041
7   9  19811.124       0.124            288.697           2.123
8  10  19213.949       0.127            272.178           1.918
```



SECTION 5: CLUSTER VISUALIZATION & INTERPRETATION

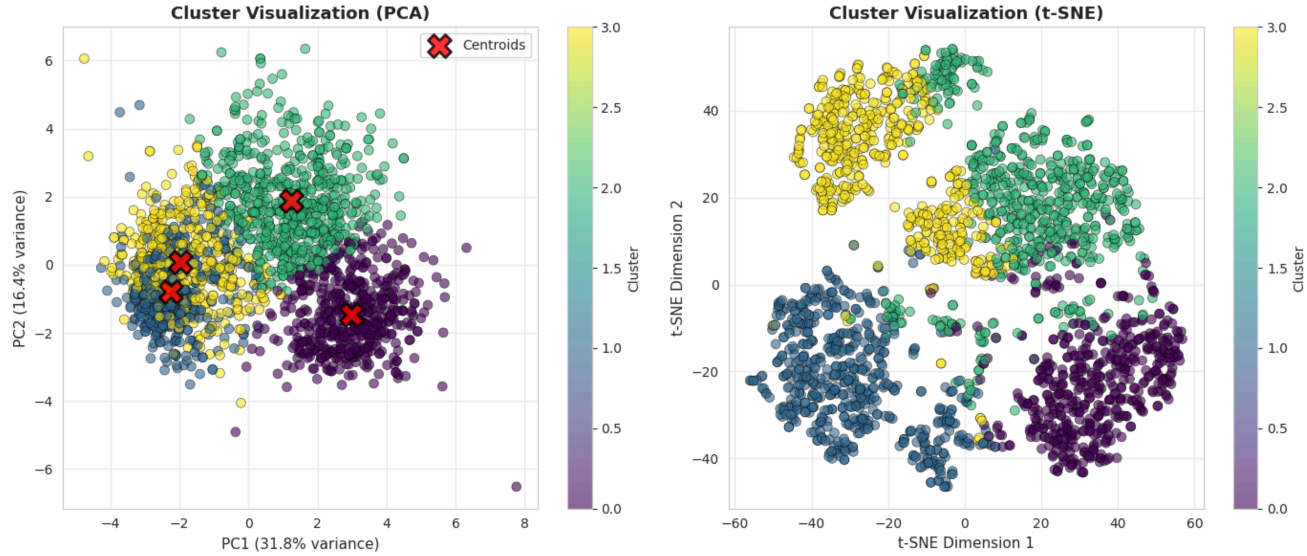
```
print("="*80)
print("CLUSTER VISUALIZATION & ANALYSIS")
print("="*80)

# 5.1 Dimensionality Reduction for Visualization

# PCA Visualization
print("\n Performing PCA for 2D visualization...")
pca = PCA(n_components=2, random_state=42)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(14, 6))

# PCA Plot
plt.subplot(1, 2, 1)
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1],
                      c=df['Cluster'], cmap='viridis',
                      s=50, alpha=0.6, edgecolors='black', linewidth=0.5)
plt.colorbar(scatter, label='Cluster')
plt.xlabel(f'PC1 ({pca.explained_variance_ratio_[0]*100:.1f}% variance)', fontsize=11)
plt.ylabel(f'PC2 ({pca.explained_variance_ratio_[1]*100:.1f}% variance)', fontsize=11)
plt.title('Cluster Visualization (PCA)', fontweight='bold', fontsize=13)
plt.grid(alpha=0.3)

# Cluster Centers in PCA space
centers_pca = pca.transform(final_kmeans.cluster_centers_)
plt.scatter(centers_pca[:, 0], centers_pca[:, 1],
            c='red', s=300, alpha=0.8, edgecolors='black',
            linewidth=2, marker='X', label='Centroids')
plt.legend()
```

```
# t-SNE Visualization
print(" Performing t-SNE for 2D visualization (this may take a minute)...")
tsne = TSNE(n_components=2, random_state=42, perplexity=30, n_iter=1000)
X_tsne = tsne.fit_transform(X_scaled)

plt.subplot(1, 2, 2)
scatter = plt.scatter(X_tsne[:, 0], X_tsne[:, 1],
                      c=df['Cluster'], cmap='viridis',
                      s=50, alpha=0.6, edgecolors='black', linewidth=0.5)
plt.colorbar(scatter, label='Cluster')
plt.xlabel('t-SNE Dimension 1', fontsize=11)
plt.ylabel('t-SNE Dimension 2', fontsize=11)
plt.title('Cluster Visualization (t-SNE)', fontweight='bold', fontsize=13)
plt.grid(alpha=0.3)

plt.tight_layout()
plt.show()

# 5.2 Cluster Profiles - Comprehensive Table
print("\n📋 Detailed Cluster Profiles:")

profile_features = [
    'Education_ord', 'Income', 'Age', 'Total_Spend',
    'NumWebPurchases', 'NumStorePurchases', 'NumCatalogPurchases',
    'Total_Campaign_Accepted', 'Digital_Engagement',
    'Family_Size', 'Customer_Tenure', 'Spend_per_Purchase'
]

cluster_profiles = df.groupby('Cluster')[profile_features].mean()
print(cluster_profiles.round(2))

# Save cluster profiles
cluster_profiles.to_csv('cluster_profiles.csv')
print("\n Cluster profiles saved to 'cluster_profiles.csv'")

# 5.3 Cluster Heatmap
plt.figure(figsize=(14, 8))
sns.heatmap(cluster_profiles.T, annot=True, fmt='.2f',
            cmap='YlOrRd', linewidths=0.5, cbar_kws={"shrink": 0.8})
plt.title('Cluster Feature Heatmap (Mean Values)',
          fontsize=14, fontweight='bold', pad=15)
plt.xlabel('Cluster', fontsize=12)
plt.ylabel('Feature', fontsize=12)
plt.tight_layout()
plt.show()

# 5.4 Feature Comparison Across Clusters
fig, axes = plt.subplots(3, 2, figsize=(16, 14))
fig.suptitle('Feature Comparison Across Clusters', fontsize=16, fontweight='bold')

comparison_features = [
    ('Income', 'Income ($)'),
    ('Total_Spend', 'Total Spend ($)'),
    ('Total_Campaign_Accepted', 'Campaigns Accepted'),
    ('NumWebPurchases', 'Web Purchases'),
    ('NumStorePurchases', 'Store Purchases'),
    ('Digital_Engagement', 'Digital Engagement Score')
]

for idx, (feature, label) in enumerate(comparison_features):
    row = idx // 2
    col = idx % 2
    ax = axes[row, col]

    sns.boxplot(x='Cluster', y=feature, data=df, ax=ax, palette='Set2')
    ax.set_title(label, fontweight='bold')
    ax.set_xlabel('Cluster')
    ax.set_ylabel(label)
    ax.grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()

# 5.5 Channel Preference by Cluster
channel_cols = ['NumWebPurchases', 'NumCatalogPurchases',
                'NumStorePurchases', 'NumDealsPurchases']
```

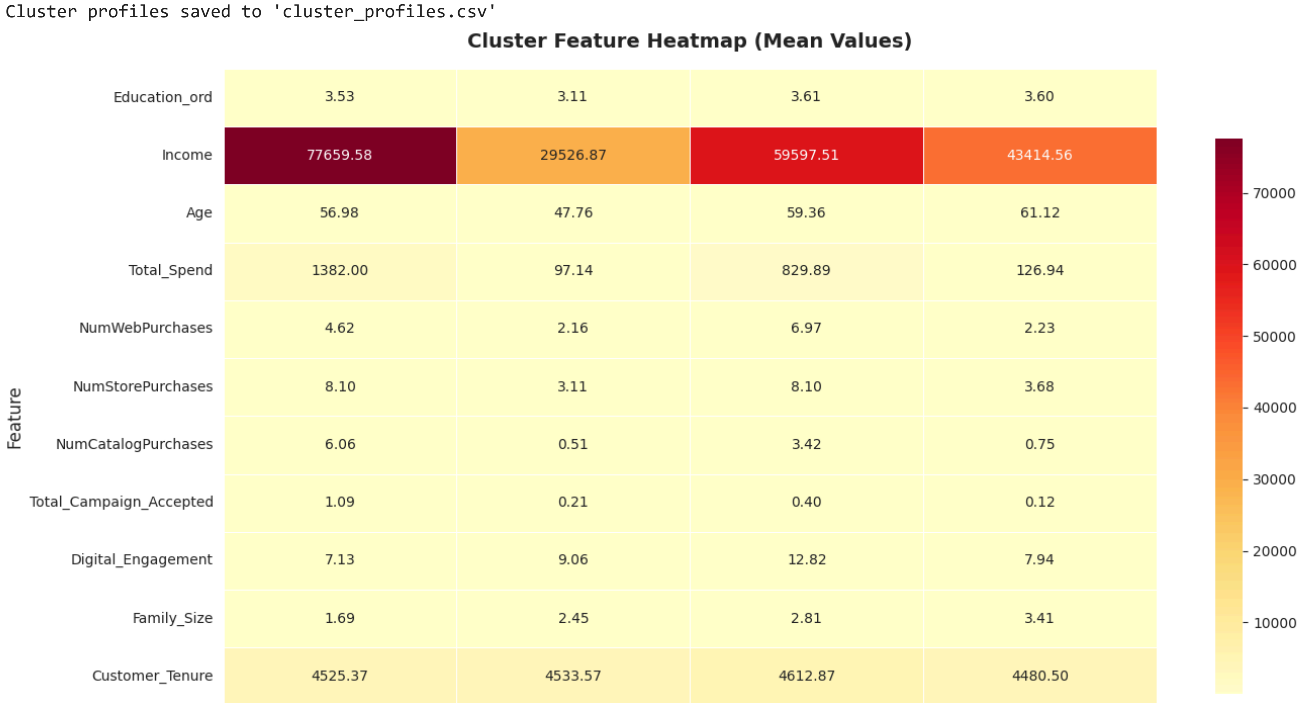
```
channel_by_cluster = df.groupby('Cluster')[channel_cols].mean()

fig, axes = plt.subplots(2, 2, figsize=(16, 12))
fig.suptitle('Purchase Channel Preferences by Cluster', fontsize=16, fontweight='bold')

for idx in range(optimal_k):
    row = idx // 2
    col = idx % 2
    ax = axes[row, col]

    cluster_data = channel_by_cluster.loc[idx]
    colors = ['#FF6B6B', '#4ECDC4', '#45B7D1', '#FFA07A']

    ax.bar(range(len(cluster_data)), cluster_data, color=colors,
           edgecolor='black', linewidth=1.5)
    ax.set_xticks(range(len(cluster_data)))
    ax.set_xticklabels(['Web', 'Catalog', 'Store', 'Deals'], rotation=0)
    ax.set_title(f'Cluster {idx}', fontweight='bold', fontsize=13)
    ax.set_ylabel('Average Purchases')
    ax.grid(axis='y', alpha=0.3)

    # Add value labels
    for i, v in enumerate(cluster_data):
        ax.text(i, v + 0.1, f'{v:.2f}', ha='center', va='bottom', fontweight='bold')

plt.tight_layout()
plt.show()

# 5.6 Spending Category Breakdown
spend_categories = ['MntWines', 'MntFruits', 'MntMeatProducts',
                    'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']
spend_by_cluster = df.groupby('Cluster')[spend_categories].mean()

fig, axes = plt.subplots(2, 2, figsize=(16, 12))
fig.suptitle('Spending by Product Category and Cluster', fontsize=16, fontweight='bold')

for idx in range(optimal_k):
    row = idx // 2
    col = idx % 2
    ax = axes[row, col]

    cluster_spend = spend_by_cluster.loc[idx]
    category_names = ['Wines', 'Fruits', 'Meat', 'Fish', 'Sweets', 'Gold']

    colors = sns.color_palette('husl', len(category_names))
    ax.pie(cluster_spend, labels=category_names, autopct='%1.1f%%',
           startangle=90, colors=colors, wedgeprops={'edgecolor': 'black'})
    ax.set_title(f'Cluster {idx} - Total: ${cluster_spend.sum():.0f}',
                 fontweight='bold', fontsize=13)

plt.tight_layout()
plt.show()

# 5.7 Cluster Summary Statistics
print("\n Comprehensive Cluster Statistics:")
print("="*80)

for cluster_id in sorted(df['Cluster'].unique()):
    cluster_data = df[df['Cluster'] == cluster_id]

    print(f"\n CLUSTER {cluster_id}")
    print(f"   Size: {len(cluster_data):,} customers ({len(cluster_data)/len(df)*100:.1f}%)")
    print(f"\n   Demographics:")
    print(f"   - Average Age: {cluster_data['Age'].mean():.1f} years")
    print(f"   - Average Income: ${cluster_data['Income'].mean():,.0f}")
    print(f"   - Education Level: {cluster_data['Education_ord'].mean():.2f}")
    print(f"   - Family Size: {cluster_data['Family_Size'].mean():.2f}")

    print(f"\n   Purchasing Behavior:")
    print(f"   - Total Spend: ${cluster_data['Total_Spend'].mean():,.2f}")
    print(f"   - Total Purchases: {cluster_data['Total_Purchases'].mean():.2f}")
    print(f"   - Spend per Purchase: ${cluster_data['Spend_per_Purchase'].mean():.2f}")
    print(f"   - Customer Tenure: {cluster_data['Customer_Tenure'].mean():.0f} days")

    print(f"\n   Channel Preferences:")
    print(f"   - Web Purchases: {cluster_data['NumWebPurchases'].mean():.2f}")
    print(f"   - Store Purchases: {cluster_data['NumStorePurchases'].mean():.2f}")
```

```
    print(f"   - Catalog Purchases: {cluster_data['NumCatalogPurchases'].mean():.2f}")

    print(f"\n   Marketing Engagement:")
    print(f"   - Campaigns Accepted: {cluster_data['Total_Campaign_Accepted'].mean():.2f}")
    print(f"   - Response Rate: {cluster_data['Campaign_Response_Rate'].mean()*100:.1f}%")
    print(f"   - Digital Engagement: {cluster_data['Digital_Engagement'].mean():.2f}")

    print("-"*80)

print("\n" + "="*80)
```

```
================================================================================
CLUSTER VISUALIZATION & ANALYSIS
================================================================================

 Performing PCA for 2D visualization...
 Performing t-SNE for 2D visualization (this may take a minute)...
```

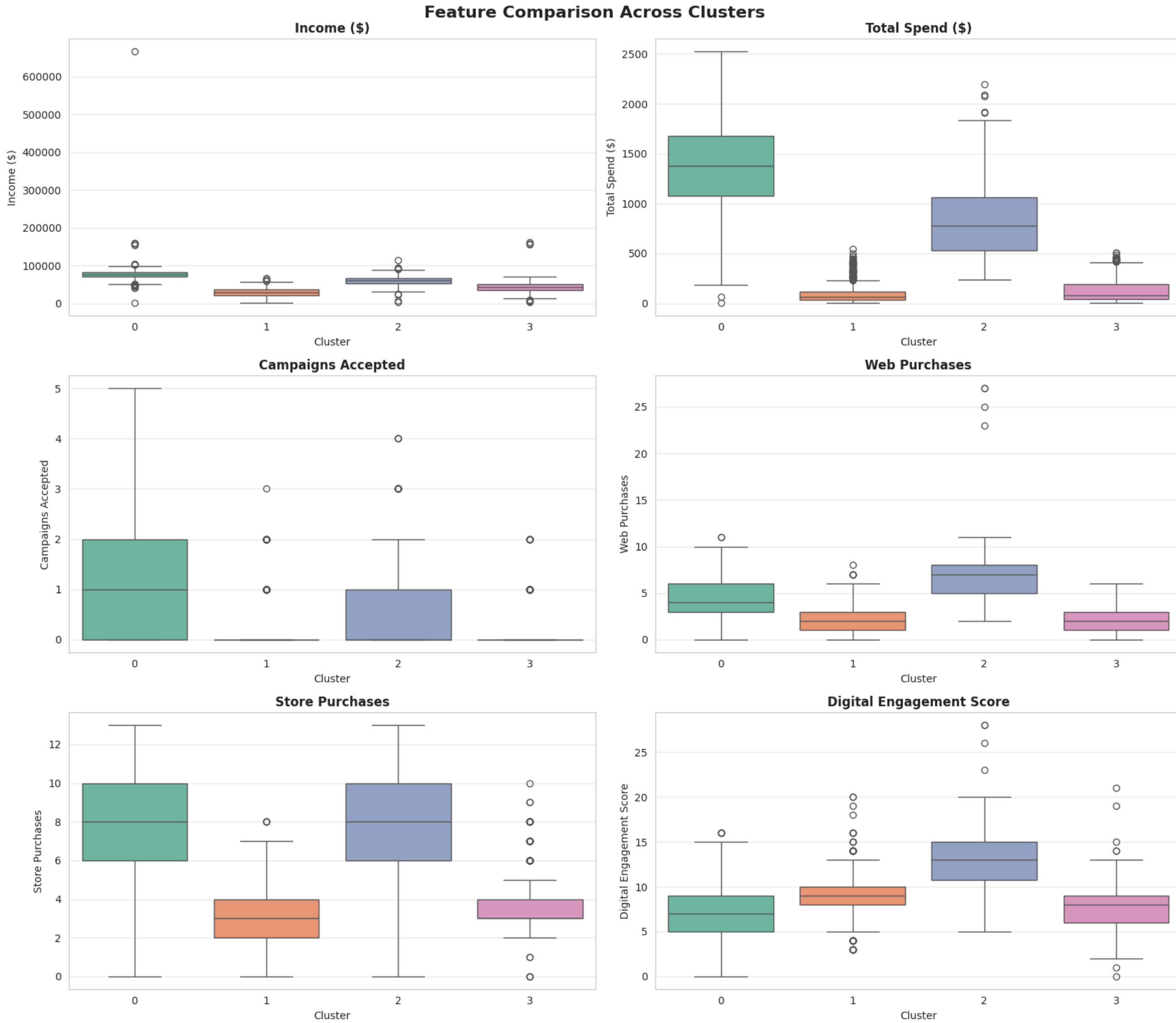


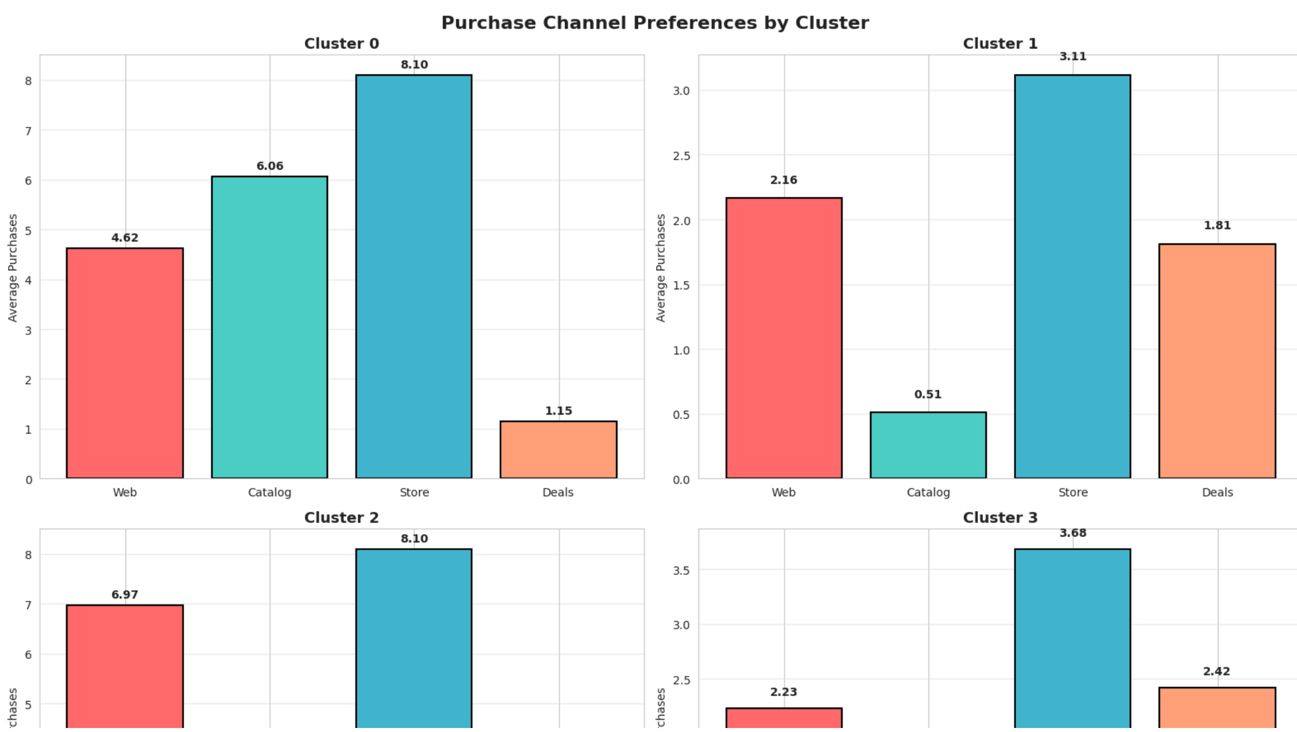

```
📋 Detailed Cluster Profiles:
         Education_ord    Income    Age  Total_Spend  NumWebPurchases  \
Cluster
0                 3.53  77659.58  56.98      1382.00             4.62
1                 3.11  29526.87  47.76        97.14             2.16
2                 3.61  59597.51  59.36       829.89             6.97
3                 3.60  43414.56  61.12       126.94             2.23

         NumStorePurchases  NumCatalogPurchases  Total_Campaign_Accepted  \
Cluster
0                     8.10                 6.06                     1.09
1                     3.11                 0.51                     0.21
2                     8.10                 3.42                     0.40
3                     3.68                 0.75                     0.12

         Digital_Engagement  Family_Size  Customer_Tenure  Spend_per_Purchase
Cluster
0                      7.13         1.69          4525.37               68.91
1                      9.06         2.45          4533.57                9.92
2                     12.82         2.81          4612.87               35.46
3                      7.94         3.41          4480.50               10.90

 Cluster profiles saved to 'cluster_profiles.csv'
```

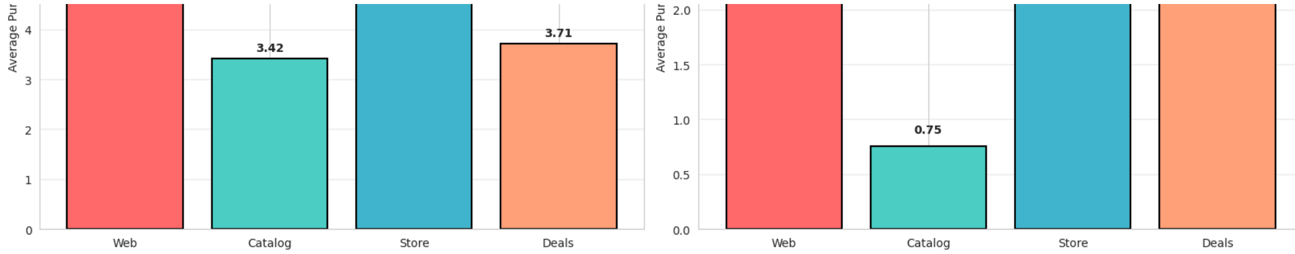


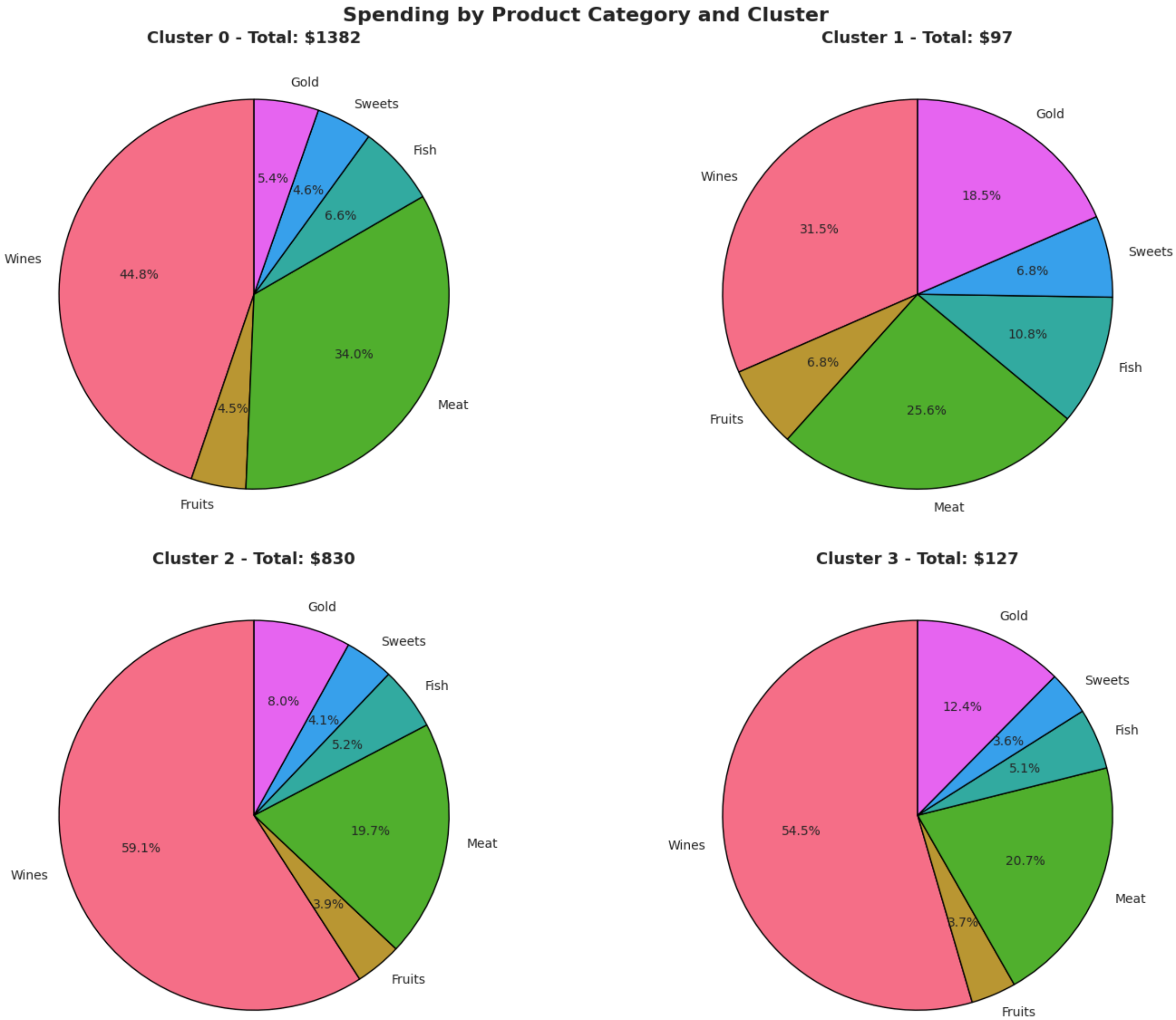
	0	1	2	3
Spend_per_Purchase	68.91	9.92	35.46	10.90

Cluster










```
Comprehensive Cluster Statistics:
================================================================================

CLUSTER 0
  Size: 519 customers (23.2%)

  Demographics:
  - Average Age: 57.0 years
  - Average Income: $77,660
  - Education Level: 3.53
  - Family Size: 1.69

  Purchasing Behavior:
  - Total Spend: $1,382.00
  - Total Purchases: 19.93
  - Spend per Purchase: $68.91
  - Customer Tenure: 4525 days

  Channel Preferences:
  - Web Purchases: 4.62
  - Store Purchases: 8.10
  - Catalog Purchases: 6.06
```

```
  Marketing Engagement:
  - Campaigns Accepted: 1.09
  - Response Rate: 18.1%
  - Digital Engagement: 7.13
--------------------------------------------------------------------------------

 CLUSTER 1
  Size: 583 customers (26.0%)

  Demographics:
  - Average Age: 47.8 years
  - Average Income: $29,527
  - Education Level: 3.11
  - Family Size: 2.45

  Purchasing Behavior:
  - Total Spend: $97.14
  - Total Purchases: 7.60
  - Spend per Purchase: $9.92
  - Customer Tenure: 4534 days

  Channel Preferences:
  - Web Purchases: 2.16
  - Store Purchases: 3.11
  - Catalog Purchases: 0.51

  Marketing Engagement:
  - Campaigns Accepted: 0.21
  - Response Rate: 3.5%
  - Digital Engagement: 9.06
--------------------------------------------------------------------------------

 CLUSTER 2
  Size: 624 customers (27.9%)

  Demographics:
  - Average Age: 59.4 years
  - Average Income: $59,598
  - Education Level: 3.61
  - Family Size: 2.81

  Purchasing Behavior:
  - Total Spend: $829.89
  - Total Purchases: 22.19
  - Spend per Purchase: $35.46
  - Customer Tenure: 4613 days

  Channel Preferences:
  - Web Purchases: 6.97
  - Store Purchases: 8.10
  - Catalog Purchases: 3.42

  Marketing Engagement:
  - Campaigns Accepted: 0.40
  - Response Rate: 6.7%
  - Digital Engagement: 12.82
--------------------------------------------------------------------------------

 CLUSTER 3
  Size: 514 customers (22.9%)

  Demographics:
  - Average Age: 61.1 years
  - Average Income: $43,415
  - Education Level: 3.60
  - Family Size: 3.41

  Purchasing Behavior:
  - Total Spend: $126.94
  - Total Purchases: 9.09
  - Spend per Purchase: $10.90
  - Customer Tenure: 4480 days

  Channel Preferences:
  - Web Purchases: 2.23
  - Store Purchases: 3.68
  - Catalog Purchases: 0.75

  Marketing Engagement:
  - Campaigns Accepted: 0.12
  - Response Rate: 2.0%
  - Digital Engagement: 7.94
--------------------------------------------------------------------------------
```

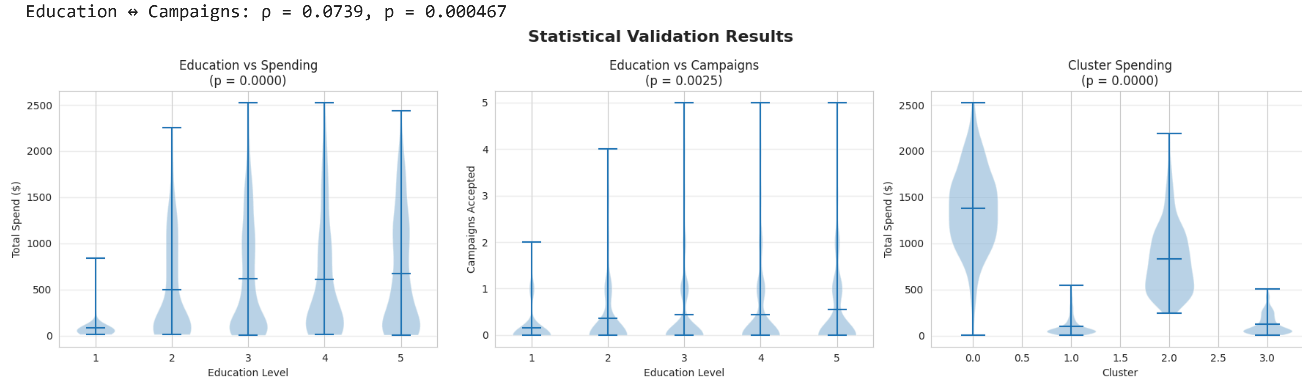
SECTION 6: STATISTICAL VALIDATION OF EDUCATION'S IMPACT

```
from scipy.stats import kruskal, mannwhitneyu
from itertools import combinations

print("="*80)
print("STATISTICAL VALIDATION")
print("="*80)

# 6.1 Education vs Spending
print("\n Test 1: Education Level vs Total Spending")
print("-"*60)

edu_levels = sorted(df['Education_ord'].unique())
spend_groups = [
    df[df['Education_ord'] == level]['Total_Spend'].dropna()
    for level in edu_levels
]

# Kruskal-Wallis test
h_stat, p_value = kruskal(*spend_groups)
print(f"Kruskal-Wallis H-test:")
print(f"  H-statistic: {h_stat:.4f}")
print(f"  P-value: {p_value:.6f}")
print(f"  Result: {'SIGNIFICANT' if p_value < 0.05 else 'NOT SIGNIFICANT'} (α = 0.05)")

if p_value < 0.05:
    print(f"\n Education level significantly impacts customer spending")

    # Post-hoc pairwise comparisons
    print(f"\n Post-hoc Pairwise Comparisons (Mann-Whitney U tests):")
    print(f"{'Comparison':<25} {'U-statistic':<15} {'P-value':<12} {'Significant'}")
    print("-"*70)

    for (level1, level2) in combinations(edu_levels, 2):
        group1 = df[df['Education_ord'] == level1]['Total_Spend'].dropna()
        group2 = df[df['Education_ord'] == level2]['Total_Spend'].dropna()

        u_stat, p_val = mannwhitneyu(group1, group2, alternative='two-sided')
        sig = "Yes" if p_val < 0.05 else "No"

        print(f"Education {level1} vs {level2:<6} {u_stat:<15.2f} {p_val:<12.6f} {sig}")

# 6.2 Education vs Campaign Response
print("\n\n Test 2: Education Level vs Campaign Response")
print("-"*60)

response_groups = [
    df[df['Education_ord'] == level]['Total_Campaign_Accepted'].dropna()
    for level in edu_levels
]

h_stat2, p_value2 = kruskal(*response_groups)
print(f"Kruskal-Wallis H-test:")
print(f"  H-statistic: {h_stat2:.4f}")
print(f"  P-value: {p_value2:.6f}")
print(f"  Result: {'SIGNIFICANT' if p_value2 < 0.05 else 'NOT SIGNIFICANT'} (α = 0.05)")

if p_value2 < 0.05:
    print(f"\n Education level significantly impacts campaign responsiveness")

# 6.3 Cluster Differences
print("\n\n Test 3: Differences Across Clusters")
print("-"*60)

cluster_groups_spend = [
    df[df['Cluster'] == cluster]['Total_Spend'].dropna()
    for cluster in sorted(df['Cluster'].unique())
]

h_stat3, p_value3 = kruskal(*cluster_groups_spend)
print(f"Kruskal-Wallis H-test (Spending across clusters):")
print(f"  H-statistic: {h_stat3:.4f}")
print(f"  P-value: {p_value3:.6f}")
```

```
print(f"  Result: {'SIGNIFICANT' if p_value3 < 0.05 else 'NOT SIGNIFICANT'} (α = 0.05)")

if p_value3 < 0.05:
    print(f"\n Clusters show significantly different spending patterns")

# 6.4 Effect Sizes
print("\n\n Effect Size Analysis")
print("-"*60)

from scipy.stats import spearmanr

# Spearman correlation (ordinal data)
corr_spend, p_spend = spearmanr(df['Education_ord'], df['Total_Spend'])
corr_income, p_income = spearmanr(df['Education_ord'], df['Income'])
corr_campaign, p_campaign = spearmanr(df['Education_ord'], df['Total_Campaign_Accepted'])

print(f"Spearman Correlations with Education Level:")
print(f"  Education ↔ Spending:  ρ = {corr_spend:.4f}, p = {p_spend:.6f}")
print(f"  Education ↔ Income:    ρ = {corr_income:.4f}, p = {p_income:.6f}")
print(f"  Education ↔ Campaigns: ρ = {corr_campaign:.4f}, p = {p_campaign:.6f}")

# 6.5 Visualization of Statistical Tests
fig, axes = plt.subplots(1, 3, figsize=(18, 5))
fig.suptitle('Statistical Validation Results', fontsize=16, fontweight='bold')

# Education vs Spending
axes[0].violinplot([df[df['Education_ord'] == level]['Total_Spend'].dropna()
                     for level in edu_levels],
                    positions=edu_levels, showmeans=True)
axes[0].set_xlabel('Education Level')
axes[0].set_ylabel('Total Spend ($)')
axes[0].set_title(f'Education vs Spending\n(p = {p_value:.4f})')
axes[0].grid(axis='y', alpha=0.3)

# Education vs Campaign Response
axes[1].violinplot([df[df['Education_ord'] == level]['Total_Campaign_Accepted'].dropna()
                     for level in edu_levels],
                    positions=edu_levels, showmeans=True)
axes[1].set_xlabel('Education Level')
axes[1].set_ylabel('Campaigns Accepted')
axes[1].set_title(f'Education vs Campaigns\n(p = {p_value2:.4f})')
axes[1].grid(axis='y', alpha=0.3)

# Cluster Spending Distribution
axes[2].violinplot([df[df['Cluster'] == c]['Total_Spend'].dropna()
                     for c in sorted(df['Cluster'].unique())],
                    positions=sorted(df['Cluster'].unique()), showmeans=True)
axes[2].set_xlabel('Cluster')
axes[2].set_ylabel('Total Spend ($)')
axes[2].set_title(f'Cluster Spending\n(p = {p_value3:.4f})')
axes[2].grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()

print("\n" + "="*80)
```

```
================================================================================
STATISTICAL VALIDATION
================================================================================

 Test 1: Education Level vs Total Spending
------------------------------------------------------------
Kruskal-Wallis H-test:
  H-statistic: 71.0185
  P-value: 0.000000
  Result: SIGNIFICANT (α = 0.05)

 Education level significantly impacts customer spending

 Post-hoc Pairwise Comparisons (Mann-Whitney U tests):
Comparison                U-statistic     P-value      Significant
----------------------------------------------------------------------
Education 1 vs 2      2685.00         0.000000     Yes
Education 1 vs 3      12091.50        0.000000     Yes
Education 1 vs 4      3610.00         0.000000     Yes
Education 1 vs 5      4667.00         0.000000     Yes
Education 2 vs 3      100800.00       0.006979     Yes
Education 2 vs 4      33111.50        0.019076     Yes
Education 2 vs 5      41108.50        0.000558     Yes
Education 3 vs 4      209171.00       0.925406     No
Education 3 vs 5      259797.50       0.101324     No
Education 4 vs 5      84623.00        0.140158     No


 Test 2: Education Level vs Campaign Response
------------------------------------------------------------
Kruskal-Wallis H-test:
  H-statistic: 16.4120
  P-value: 0.002513
  Result: SIGNIFICANT (α = 0.05)

 Education level significantly impacts campaign responsiveness
```

```
 Test 3: Differences Across Clusters
------------------------------------------------------------
Kruskal-Wallis H-test (Spending across clusters):
  H-statistic: 1745.1113
  P-value: 0.000000
  Result: SIGNIFICANT (α = 0.05)

 Clusters show significantly different spending patterns


 Effect Size Analysis
------------------------------------------------------------
Spearman Correlations with Education Level:
  Education ↔ Spending:  ρ = 0.1040, p = 0.000001
  Education ↔ Income:    ρ = 0.1527, p = 0.000000
  Education ↔ Campaigns: ρ = 0.0739, p = 0.000467
```




```
================================================================================
```

SECTION 7: MARKETING STRATEGY IMPLEMENTATION

```
print("="*80)
print("PERSONALIZED MARKETING STRATEGY IMPLEMENTATION")
```

```
print("="*80)

# 7.1 Marketing Strategy Engine
class MarketingStrategyEngine:
    """
    Assigns personalized marketing strategies to customer segments
    """

    def __init__(self):
        self.strategies = {
            0: {
                'segment_name': 'Budget-Conscious Educated',
                'description': 'Educated but income-constrained customers',
                'channels': ['Email', 'Newsletter'],
                'offer_type': 'Discount & Value Bundles',
                'messaging': 'Value-for-money, practical benefits',
                'frequency': 'Monthly',
                'budget_allocation': 0.15,
                'expected_response_rate': 0.08,
                'recommended_discount': '15-20%'
            },
            1: {
                'segment_name': 'Digital Mid-Value',
                'description': 'Digitally active omnichannel shoppers',
                'channels': ['App Notifications', 'Email', 'Retargeting Ads'],
                'offer_type': 'Cross-sell & Product Bundles',
                'messaging': 'Convenience, variety, seamless experience',
                'frequency': 'Bi-weekly',
                'budget_allocation': 0.35,
                'expected_response_rate': 0.18,
                'recommended_discount': '10-15%'
            },
            2: {
                'segment_name': 'Premium High-Value',
                'description': 'Highest value, highly responsive customers',
                'channels': ['Personalized Email', 'Premium Catalog', 'VIP Events'],
                'offer_type': 'Exclusive Products & Loyalty Rewards',
                'messaging': 'Quality, exclusivity, sophistication',
                'frequency': 'Monthly (premium)',
                'budget_allocation': 0.40,
                'expected_response_rate': 0.35,
                'recommended_discount': '5-10% (or exclusive access)'
            },
            3: {
                'segment_name': 'Traditional Price-Sensitive',
                'description': 'Low income, store-centric, price-focused',
                'channels': ['SMS', 'In-store Signage', 'Local Ads'],
                'offer_type': 'Clear Price Discounts',
                'messaging': 'Immediate savings, affordability',
                'frequency': 'Event-based (seasonal)',
                'budget_allocation': 0.10,
                'expected_response_rate': 0.06,
                'recommended_discount': '20-25%'
            }
        }

    def get_strategy(self, cluster_id):
        """Get strategy for a specific cluster"""
        return self.strategies.get(cluster_id, None)

    def assign_strategies(self, dataframe):
        """Apply strategies to entire dataframe"""
        df_copy = dataframe.copy()

        df_copy['Segment_Name'] = df_copy['Cluster'].map(
            lambda x: self.strategies[x]['segment_name']
        )
        df_copy['Primary_Channel'] = df_copy['Cluster'].map(
            lambda x: ', '.join(self.strategies[x]['channels'][:2])
        )
        df_copy['Offer_Type'] = df_copy['Cluster'].map(
            lambda x: self.strategies[x]['offer_type']
        )
        df_copy['Contact_Frequency'] = df_copy['Cluster'].map(
            lambda x: self.strategies[x]['frequency']
        )
```

```
        return df_copy

    def print_strategy_summary(self):
        """Print comprehensive strategy summary"""
        print("\n MARKETING STRATEGY SUMMARY")
        print("="*80)

        for cluster_id, strategy in self.strategies.items():
            print(f"\n CLUSTER {cluster_id}: {strategy['segment_name']}")
            print(f"   Description: {strategy['description']}")
            print(f"\n   Recommended Strategy:")
            print(f"   • Channels: {', '.join(strategy['channels'])}")
            print(f"   • Offer Type: {strategy['offer_type']}")
            print(f"   • Messaging: {strategy['messaging']}")
            print(f"   • Frequency: {strategy['frequency']}")
            print(f"   • Budget Allocation: {strategy['budget_allocation']*100:.0f}%")
            print(f"   • Expected Response: {strategy['expected_response_rate']*100:.0f}%")
            print(f"   • Discount Range: {strategy['recommended_discount']}")
            print("-"*80)

# 7.2 Initialize Strategy Engine
strategy_engine = MarketingStrategyEngine()

# Print strategy summary
strategy_engine.print_strategy_summary()

# 7.3 Apply Strategies to DataFrame
df_with_strategy = strategy_engine.assign_strategies(df)

print("\n Marketing strategies assigned to all customers")
print(f"\nSample of customer assignments:")
print(df_with_strategy[['Cluster', 'Segment_Name', 'Primary_Channel',
                         'Offer_Type', 'Total_Spend']].head(10))

# Save customer segments with strategies
df_with_strategy.to_csv('customer_segments_with_strategies.csv', index=False)
print("\n Customer segments saved to 'customer_segments_with_strategies.csv'")

# 7.4 Strategy Allocation Visualization
fig, axes = plt.subplots(1, 2, figsize=(16, 6))
fig.suptitle('Marketing Budget & Channel Allocation', fontsize=16, fontweight='bold')

# Budget allocation
budget_data = [strategy_engine.strategies[i]['budget_allocation']
               for i in range(optimal_k)]
segment_names = [strategy_engine.strategies[i]['segment_name']
                 for i in range(optimal_k)]

colors = ['#FF6B6B', '#4ECDC4', '#45B7D1', '#FFA07A']
axes[0].pie(budget_data, labels=segment_names, autopct='%1.0f%%',
            startangle=90, colors=colors, wedgeprops={'edgecolor': 'black', 'linewidth': 2})
axes[0].set_title('Marketing Budget Allocation by Segment', fontweight='bold')

# Expected ROI comparison
cluster_sizes = df['Cluster'].value_counts().sort_index()
expected_responses = [cluster_sizes[i] * strategy_engine.strategies[i]['expected_response_rate']
                      for i in range(optimal_k)]

axes[1].bar(segment_names, expected_responses, color=colors, edgecolor='black', linewidth=1.5)
axes[1].set_xlabel('Segment', fontsize=12)
axes[1].set_ylabel('Expected Responses', fontsize=12)
axes[1].set_title('Expected Campaign Responses by Segment', fontweight='bold')
axes[1].tick_params(axis='x', rotation=15)
axes[1].grid(axis='y', alpha=0.3)

for i, v in enumerate(expected_responses):
    axes[1].text(i, v + 5, f'{v:.0f}', ha='center', va='bottom', fontweight='bold')

plt.tight_layout()
plt.show()

# 7.5 Calculate Expected ROI
print("\n EXPECTED ROI ANALYSIS")
print("="*80)

# Assumptions
total_marketing_budget = 100000  # $100,000
```

```
avg_order_margin = 0.30  # 30% profit margin
campaign_cost_per_contact = 2.50  # $2.50 per customer contact

for cluster_id in range(optimal_k):
    strategy = strategy_engine.strategies[cluster_id]
    cluster_size = cluster_sizes[cluster_id]

    # Calculate expected outcomes
    budget_allocated = total_marketing_budget * strategy['budget_allocation']
    contacts_affordable = budget_allocated / campaign_cost_per_contact
    expected_responses = contacts_affordable * strategy['expected_response_rate']
    avg_order_value = df[df['Cluster'] == cluster_id]['Total_Spend'].mean()
    expected_revenue = expected_responses * avg_order_value
    expected_profit = expected_revenue * avg_order_margin
    roi = ((expected_profit - budget_allocated) / budget_allocated) * 100

    print(f"\n Cluster {cluster_id}: {strategy['segment_name']}")
    print(f"   Customers: {cluster_size:,}")
    print(f"   Budget: ${budget_allocated:,.0f} ({strategy['budget_allocation']*100:.0f}%)")
    print(f"   Contacts: {contacts_affordable:,.0f}")
    print(f"   Expected Responses: {expected_responses:,.0f} ({strategy['expected_response_rate']*100:.0f}%)")
    print(f"   Avg Order Value: ${avg_order_value:,.2f}")
    print(f"   Expected Revenue: ${expected_revenue:,.0f}")
    print(f"   Expected Profit: ${expected_profit:,.0f}")
    print(f"   ROI: {roi:,.1f}%")
    print("-"*80)

print("\n" + "="*80)
```

```
================================================================================
PERSONALIZED MARKETING STRATEGY IMPLEMENTATION
================================================================================

 MARKETING STRATEGY SUMMARY
================================================================================

 CLUSTER 0: Budget-Conscious Educated
   Description: Educated but income-constrained customers

   Recommended Strategy:
   • Channels: Email, Newsletter
   • Offer Type: Discount & Value Bundles
   • Messaging: Value-for-money, practical benefits
   • Frequency: Monthly
   • Budget Allocation: 15%
   • Expected Response: 8%
   • Discount Range: 15-20%
--------------------------------------------------------------------------------

 CLUSTER 1: Digital Mid-Value
   Description: Digitally active omnichannel shoppers

   Recommended Strategy:
   • Channels: App Notifications, Email, Retargeting Ads
   • Offer Type: Cross-sell & Product Bundles
   • Messaging: Convenience, variety, seamless experience
   • Frequency: Bi-weekly
   • Budget Allocation: 35%
   • Expected Response: 18%
   • Discount Range: 10-15%
--------------------------------------------------------------------------------

 CLUSTER 2: Premium High-Value
   Description: Highest value, highly responsive customers

   Recommended Strategy:
   • Channels: Personalized Email, Premium Catalog, VIP Events
   • Offer Type: Exclusive Products & Loyalty Rewards
   • Messaging: Quality, exclusivity, sophistication
   • Frequency: Monthly (premium)
   • Budget Allocation: 40%
   • Expected Response: 35%
   • Discount Range: 5-10% (or exclusive access)
--------------------------------------------------------------------------------

 CLUSTER 3: Traditional Price-Sensitive
   Description: Low income, store-centric, price-focused

   Recommended Strategy:
   • Channels: SMS, In-store Signage, Local Ads
   • Offer Type: Clear Price Discounts
   • Messaging: Immediate savings, affordability
   • Frequency: Event-based (seasonal)
   • Budget Allocation: 10%
   • Expected Response: 6%
   • Discount Range: 20-25%
--------------------------------------------------------------------------------

 Marketing strategies assigned to all customers

Sample of customer assignments:
   Cluster                 Segment_Name                      Primary_Channel  \
0        0    Budget-Conscious Educated                    Email, Newsletter
1        3  Traditional Price-Sensitive              SMS, In-store Signage
2        2           Premium High-Value  Personalized Email, Premium Catalog
3        1            Digital Mid-Value             App Notifications, Email
4        2           Premium High-Value  Personalized Email, Premium Catalog
5        2           Premium High-Value  Personalized Email, Premium Catalog
6        2           Premium High-Value  Personalized Email, Premium Catalog
7        1            Digital Mid-Value             App Notifications, Email
8        1            Digital Mid-Value             App Notifications, Email
9        3  Traditional Price-Sensitive              SMS, In-store Signage

                             Offer_Type  Total_Spend
0             Discount & Value Bundles         1617
1                 Clear Price Discounts           27
2  Exclusive Products & Loyalty Rewards          776
3          Cross-sell & Product Bundles           53
4  Exclusive Products & Loyalty Rewards          422
5  Exclusive Products & Loyalty Rewards          716
6  Exclusive Products & Loyalty Rewards          590
7          Cross-sell & Product Bundles          169
```

SECTION 8: A/B TESTING FRAMEWORK & SIMULATION