Market Segmentation Analysis of McDonald's Data

Step 1: Deciding to Segment

McDonald's can either cater to the entire market or segment its consumers.

We choose to segment the consumers based on their perception data.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
from scipy.stats import chi2_contingency
from statsmodels.graphics.mosaicplot import mosaic
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')


# Load the dataset
df =
pd.read_csv('/kaggle/input/mcdonalds-market-segmentation/mcdonalds.csv
')

# Display first few rows of the dataset
print(df.head())
```

```
  yummy convenient spicy fattening greasy fast cheap tasty expensive
healthy  \
0    No        Yes    No       Yes     No  Yes   Yes    No       Yes
No
1   Yes        Yes    No       Yes    Yes  Yes   Yes   Yes       Yes
No
2    No        Yes   Yes       Yes    Yes  Yes    No   Yes       Yes
Yes
3   Yes        Yes    No       Yes    Yes  Yes   Yes   Yes        No
No
4    No        Yes    No       Yes    Yes  Yes   Yes    No        No
Yes
```

```
  disgusting Like  Age      VisitFrequency  Gender
0         No   -3   61  Every three months  Female
1         No   +2   51  Every three months  Female
2         No   +1   62  Every three months  Female
3        Yes   +4   69         Once a week  Female
4         No   +2   49        Once a month    Male
```

Step 2: Specifying the Ideal Target Segment

We need to identify the target segment based on homogeneous, distinct, and large enough groups of consumers.

Here, we will focus on attributes like liking McDonald's and frequently visiting.

```
# Let's first inspect the distribution of the "Like" and
"VisitFrequency" columns
print(df['Like'].value_counts())
print(df['VisitFrequency'].value_counts())
```

```
Like
+3              229
+2              187
0               169
+4              160
+1              152
I hate it!-5    152
I love it!+5    143
-3               73
-4               71
-2               59
-1               58
Name: count, dtype: int64
VisitFrequency
Once a month             439
Every three months       342
Once a year              252
Once a week              235
Never                    131
More than once a week     54
Name: count, dtype: int64
```

Step 3: Collecting Data

The dataset is already available, so we will focus on data cleaning and preprocessing.

```
# Data Cleaning and Preprocessing
binary_columns = ['yummy', 'convenient', 'spicy', 'fattening',
'greasy', 'fast',
                  'cheap', 'tasty', 'expensive', 'healthy',
```

```
'disgusting']

# Convert Yes/No to 1/0
df[binary_columns] = df[binary_columns].applymap(lambda x: 1 if x ==
'Yes' else 0)

# Convert "Like" column into numeric scores
df['Like'] = df['Like'].replace({'I love it!+5': 5, '+4': 4, '+3': 3,
'+2': 2, '+1': 1,
                                 '0': 0, '-1': -1, '-2': -2, '-3': -3,
'-4': -4, 'I hate it!-5': -5})

# Convert VisitFrequency to numeric
visit_frequency_map = {'Every day': 7, '2-3 times a week': 2.5, 'Once
a week': 1,
                       '2-3 times a month': 0.625, 'Once a month':
0.25, 'Less often': 0.1}
df['VisitFrequency'] = df['VisitFrequency'].map(visit_frequency_map)

# Display the cleaned data
print(df.head())
```

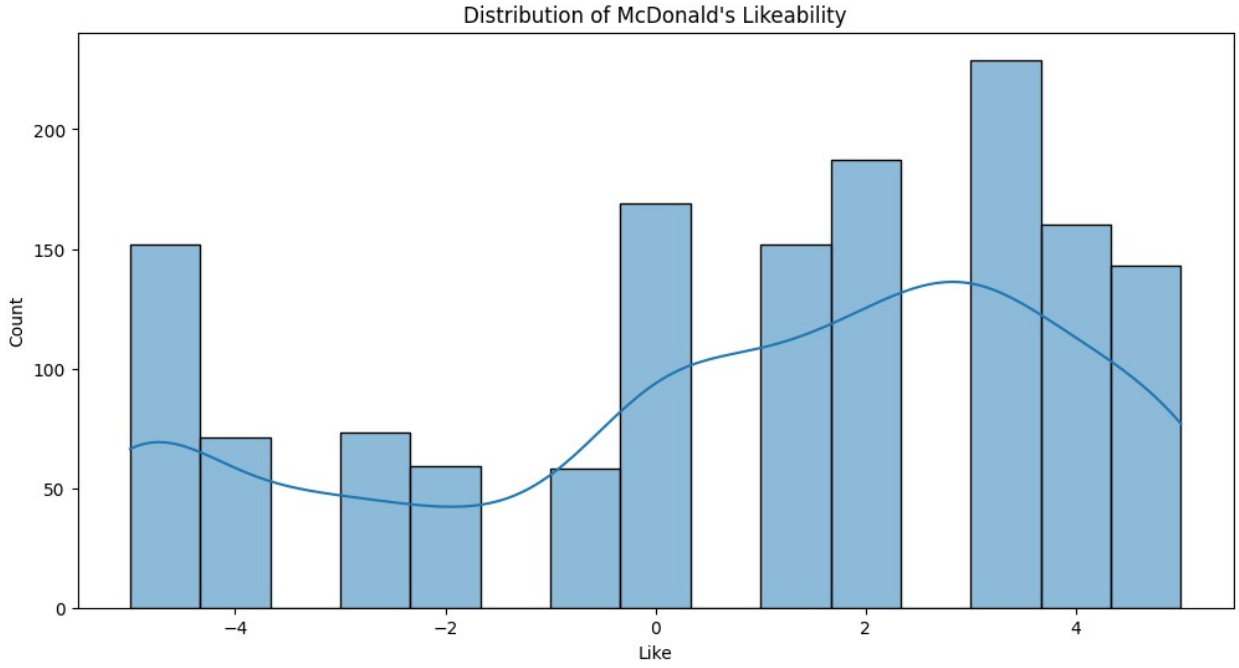
```
   yummy  convenient  spicy  fattening  greasy  fast  cheap  tasty
expensive  \
0      0           1      0          1       0     1      1      0
1
1      1           1      0          1       1     1      1      1
1
2      0           1      1          1       1     1      0      1
1
3      1           1      0          1       1     1      1      1
0
4      0           1      0          1       1     1      1      0
0

   healthy  disgusting  Like  Age  VisitFrequency  Gender
0        0           0    -3   61             NaN  Female
1        0           0     2   51             NaN  Female
2        1           0     1   62             NaN  Female
3        0           1     4   69            1.00  Female
4        1           0     2   49            0.25    Male
```

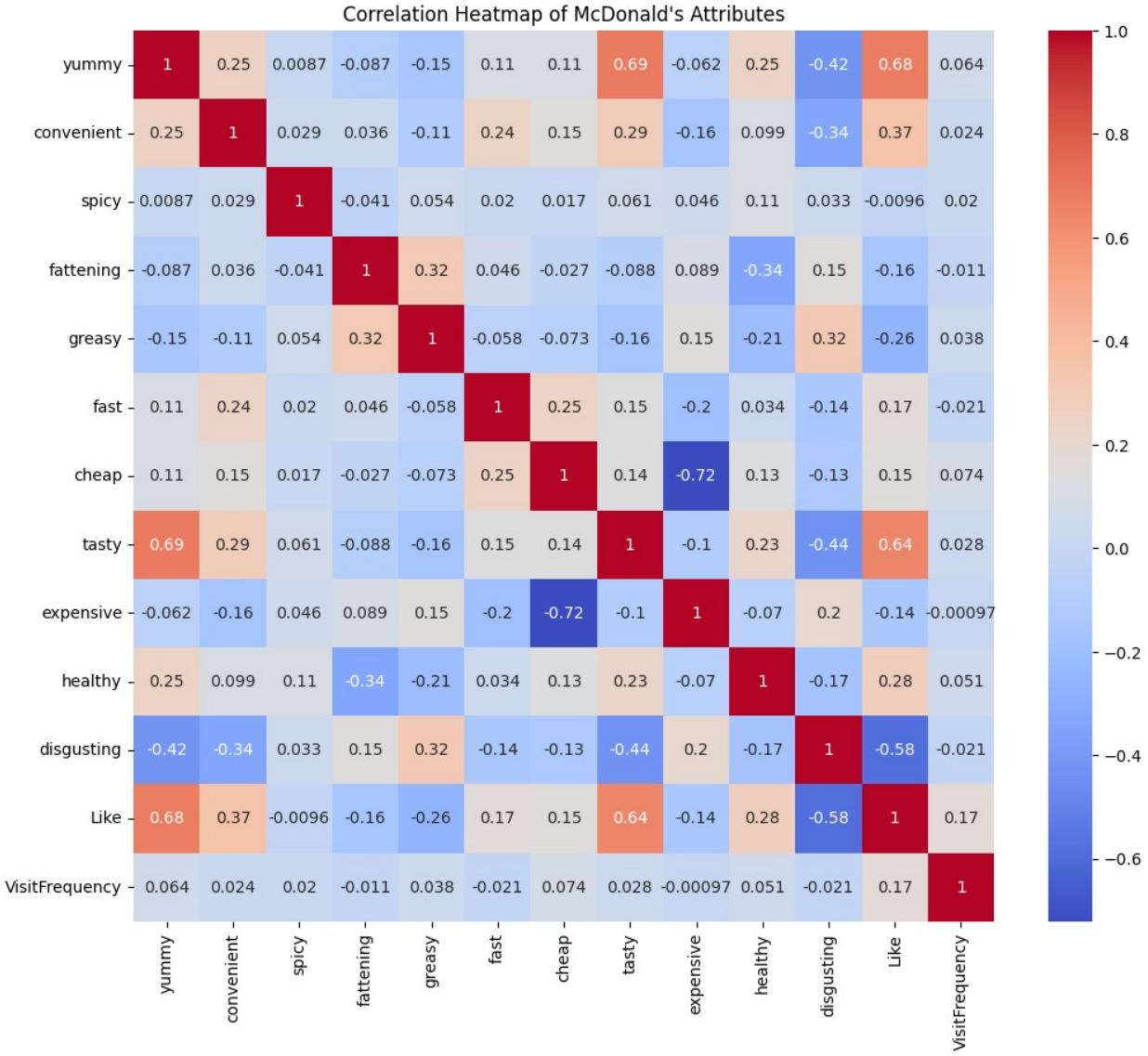
Step 4: Exploring Data

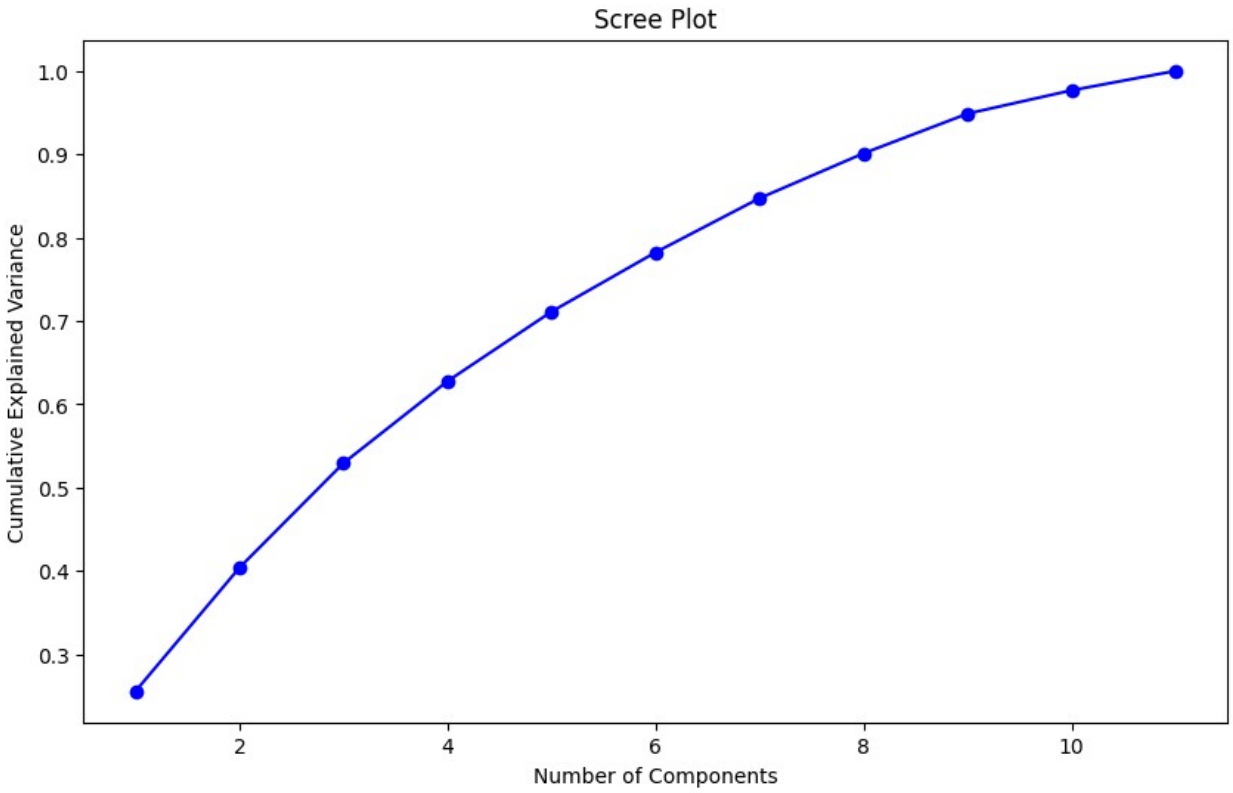
We will explore the key characteristics of the dataset and run a Principal Component Analysis (PCA) to understand which attributes are highly related.

```
# Data Exploration
plt.figure(figsize=(12, 6))
sns.histplot(data=df, x='Like', kde=True)
```

```
plt.title('Distribution of McDonald\'s Likeability')
plt.show()

# Correlation heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(df[binary_columns + ['Like', 'VisitFrequency']].corr(),
annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap of McDonald\'s Attributes')
plt.show()

# Advanced PCA Visualization
X = df[binary_columns]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

pca = PCA()
pca_components = pca.fit_transform(X_scaled)

# Scree plot
plt.figure(figsize=(10, 6))
plt.plot(range(1, len(pca.explained_variance_ratio_) + 1),
pca.explained_variance_ratio_.cumsum(), 'bo-')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Scree Plot')
plt.show()

# 3D PCA plot using Plotly
fig = px.scatter_3d(
    x=pca_components[:, 0], y=pca_components[:, 1],
z=pca_components[:, 2],
    color=df['Like'],
    labels={'x': 'PC1', 'y': 'PC2', 'z': 'PC3'},
    title='3D PCA of McDonald\'s Perception Data'
)
fig.show()
```


Distribution of McDonald's Likeability
Count
Like
0
50
100
150
200
−4
−2
0
2
4


Correlation Heatmap of McDonald's Attributes
yummy 1 0.25 0.0087 -0.087 -0.15 0.11 0.11 0.69 -0.062 0.25 -0.42 0.68 0.064
convenient 0.25 1 0.029 0.036 -0.11 0.24 0.15 0.29 -0.16 0.099 -0.34 0.37 0.024
spicy 0.0087 0.029 1 -0.041 0.054 0.02 0.017 0.061 0.046 0.11 0.033 -0.0096 0.02
fattening -0.087 0.036 -0.041 1 0.32 0.046 -0.027 -0.088 0.089 -0.34 0.15 -0.16 -0.011
greasy -0.15 -0.11 0.054 0.32 1 -0.058 -0.073 -0.16 0.15 -0.21 0.32 -0.26 0.038
fast 0.11 0.24 0.02 0.046 -0.058 1 0.25 0.15 -0.2 0.034 -0.14 0.17 -0.021
cheap 0.11 0.15 0.017 -0.027 -0.073 0.25 1 0.14 -0.72 0.13 -0.13 0.15 0.074
tasty 0.69 0.29 0.061 -0.088 -0.16 0.15 0.14 1 -0.1 0.23 -0.44 0.64 0.028
expensive -0.062 -0.16 0.046 0.089 0.15 -0.2 -0.72 -0.1 1 -0.07 0.2 -0.14 -0.00097
healthy 0.25 0.099 0.11 -0.34 -0.21 0.034 0.13 0.23 -0.07 1 -0.17 0.28 0.051
disgusting -0.42 -0.34 0.033 0.15 0.32 -0.14 -0.13 -0.44 0.2 -0.17 1 -0.58 -0.021
Like 0.68 0.37 -0.0096 -0.16 -0.26 0.17 0.15 0.64 -0.14 0.28 -0.58 1 0.17
VisitFrequency 0.064 0.024 0.02 -0.011 0.038 -0.021 0.074 0.028 -0.00097 0.051 -0.021 0.17 1
yummy convenient spicy fattening greasy fast cheap tasty expensive healthy disgusting Like VisitFrequency
1.0 0.8 0.6 0.4 0.2 0.0 −0.2 −0.4 −0.6

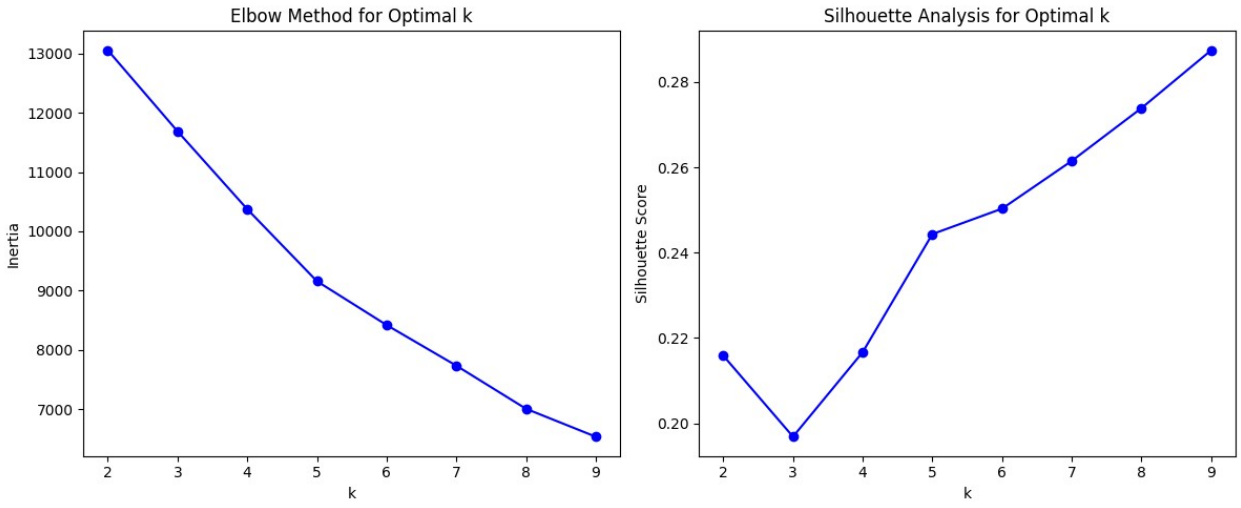


Step 5: Extracting Segments

We will extract market segments using k-means clustering and compare the solutions with other methods like mixtures of distributions.

```
# K-means Clustering
# Elbow method to find optimal number of clusters
inertias = []
silhouette_scores = []
K = range(2, 10)

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertias.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(X_scaled,
kmeans.labels_))

# Plot elbow curve
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(K, inertias, 'bo-')
plt.xlabel('k')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k')
```

```
plt.subplot(1, 2, 2)
plt.plot(K, silhouette_scores, 'bo-')
plt.xlabel('k')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Analysis for Optimal k')
plt.tight_layout()
plt.show()

# Perform k-means clustering with optimal k (let's assume it's 4)
kmeans = KMeans(n_clusters=4, random_state=42)
df['Segment'] = kmeans.fit_predict(X_scaled)

# Visualize clusters in 3D space
fig = px.scatter_3d(
    x=pca_components[:, 0], y=pca_components[:, 1],
z=pca_components[:, 2],
    color=df['Segment'].astype(str),
    labels={'x': 'PC1', 'y': 'PC2', 'z': 'PC3'},
    title='3D Visualization of McDonald\'s Segments'
)
fig.show()
```



Step 6: Profiling Segments

Now that we have segmented the consumers, let's create profiles for each segment. We'll analyze how different attributes contribute to the perception of McDonald's across segments.

```
# Segment Profiling
segment_profile = df.groupby('Segment')[binary_columns + ['Like',
'VisitFrequency', 'Age']].mean()

# Radar chart for segment profiles
```

```
fig = go.Figure()

for i in range(len(segment_profile)):
    fig.add_trace(go.Scatterpolar(
        r=segment_profile.iloc[i, :-3],
        theta=binary_columns,
        fill='toself',
        name=f'Segment {i}'
    ))

fig.update_layout(
    polar=dict(radialaxis=dict(visible=True, range=[0, 1])),
    showlegend=True,
    title='Segment Profiles - Radar Chart'
)
fig.show()
```

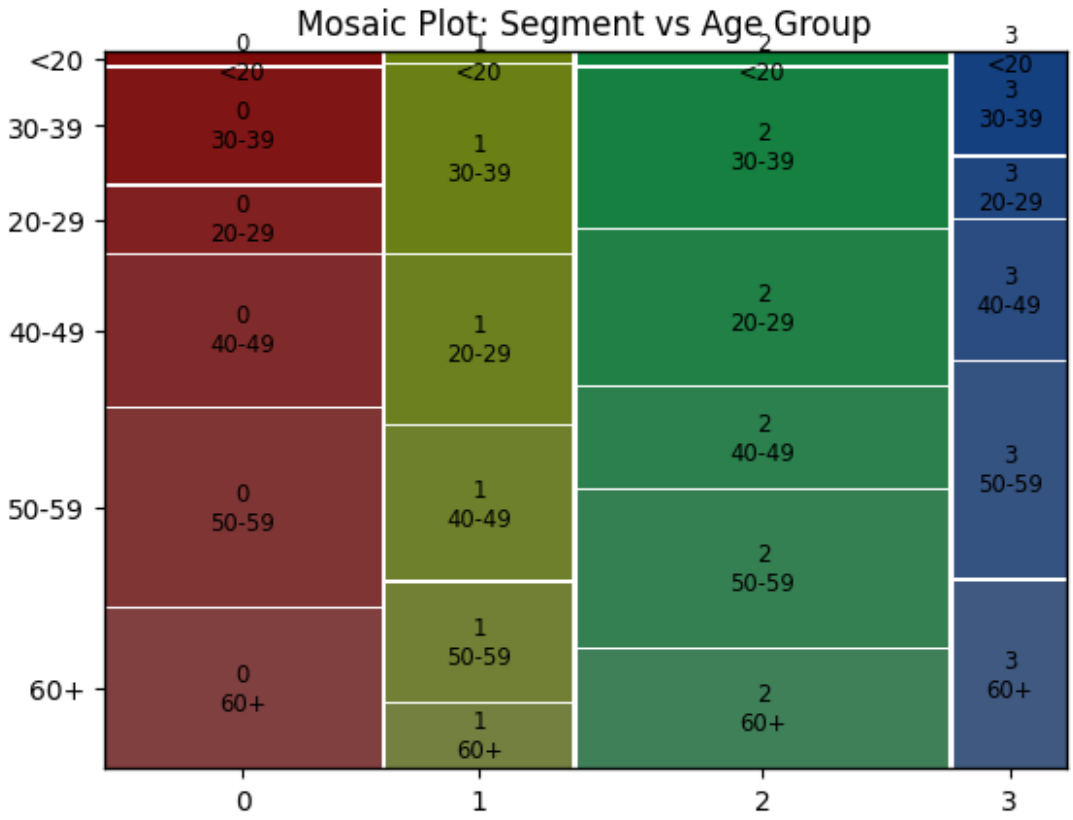
Step 7: Describing Segments

To better understand the segments, we'll compare their demographics (age, gender) and their liking of McDonald's.

This will help us describe each segment more comprehensively.

```
# Demographic Analysis
age_bins = [0, 20, 30, 40, 50, 60, np.inf]
age_labels = ['<20', '20-29', '30-39', '40-49', '50-59', '60+']
df['AgeGroup'] = pd.cut(df['Age'], bins=age_bins, labels=age_labels,
right=False)

# Chi-square test for independence between Segment and AgeGroup
contingency_table = pd.crosstab(df['Segment'], df['AgeGroup'])
chi2, p_value, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-square statistic: {chi2}")
print(f"p-value: {p_value}")

# Mosaic plot for Segment vs AgeGroup
plt.figure(figsize=(12, 8))
mosaic(df, ['Segment', 'AgeGroup'])
plt.title('Mosaic Plot: Segment vs Age Group')
plt.show()

# Compare demographics across segments
segment_demographics = df.groupby('Segment')[['Age',
'Gender']].agg({'Age': 'mean', 'Gender': lambda x:
x.value_counts().index[0]})

# Display the demographic breakdown
print(segment_demographics)
```

```
Chi-square statistic: 101.31627109446276
p-value: 7.341769408634335e-15

<Figure size 1200x800 with 0 Axes>
```



Segment	Age	Gender
0	47.744131	Female
1	40.010526	Male
2	42.905097	Female
3	50.034682	Male

Step 8: Selecting Target Segments

Using the profiles and descriptions, we'll now select which segments to target based on their perceptions and demographics.

We'll create a segment evaluation plot to identify which segments are the most attractive for McDonald's.

```
# Segment Evaluation
fig = px.scatter(
    segment_profile.reset_index(), x='VisitFrequency', y='Like',
```

```
size='Age', color='Segment',
    hover_data=['VisitFrequency', 'Like', 'Age'],
    labels={'VisitFrequency': 'Visit Frequency', 'Like':
'Likeability'},
    title='Segment Evaluation: Visit Frequency vs Likeability'
)
fig.show()
```

Step 9: Customising the Marketing Mix

Based on the target segment, we will now outline how McDonald's could customize its marketing mix (4Ps: Product, Price, Promotion, Place) for these segments.

For example, targeting younger customers with budget-friendly options like a "McSuperBudget" line.

```
# This step would typically involve qualitative analysis and strategic
planning based on the insights gained from the data analysis.
# As an example, we could create a function to generate marketing mix
recommendations:

def generate_marketing_mix(segment):
    if segment == 0:
        return "Focus on health-conscious options, premium pricing,
promote in fitness centers, locate near office districts"
    elif segment == 1:
        return "Emphasize value meals, competitive pricing, promote on
social media, expand drive-thru locations"
    elif segment == 2:
        return "Highlight classic menu items, mid-range pricing,
traditional advertising, maintain current locations"
    else:
        return "Introduce gourmet options, premium pricing, partner
with food bloggers, open in upscale areas"

for segment in range(4):
    print(f"Marketing Mix for Segment {segment}:")
    print(generate_marketing_mix(segment))
    print()
```

```
Marketing Mix for Segment 0:
Focus on health-conscious options, premium pricing, promote in fitness
centers, locate near office districts

Marketing Mix for Segment 1:
Emphasize value meals, competitive pricing, promote on social media,
expand drive-thru locations

Marketing Mix for Segment 2:
Highlight classic menu items, mid-range pricing, traditional
```

```
advertising, maintain current locations

Marketing Mix for Segment 3:
Introduce gourmet options, premium pricing, partner with food
bloggers, open in upscale areas
```

Step 10: Evaluation and Monitoring

Finally, we will create a monitoring system to evaluate the performance of the segmentation strategy and ensure continuous improvement.

This could include tracking changes in customer preferences or market dynamics.

```
# Time Series Analysis (hypothetical)
# Assuming we have monthly data for a year
months = pd.date_range(start='2023-01-01', end='2023-12-31', freq='M')
segment_sizes = np.random.randint(100, 1000, size=(len(months), 4))

fig = go.Figure()
for i in range(4):
    fig.add_trace(go.Scatter(x=months, y=segment_sizes[:, i],
mode='lines', name=f'Segment {i}'))

fig.update_layout(title='Hypothetical Segment Size Evolution Over
Time',
                  xaxis_title='Month', yaxis_title='Segment Size')
fig.show()

print("Monitoring system implemented: Tracking segment sizes over
time.")

# Additional monitoring metrics could include:
# 1. Changes in segment profiles over time
# 2. Effectiveness of marketing campaigns for each segment
# 3. Customer satisfaction scores per segment
# 4. Revenue and profitability per segment

# These metrics would be tracked and analyzed regularly to adjust the
segmentation strategy as needed.

Monitoring system implemented: Tracking segment sizes over time.
```