Step 7

Describing Segments

Adding Demographic & Behavioral Context

McDonald's Market Segmentation Analysis

From Perceptions to People

November 9, 2025

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Abstract

Step 7 enriches segment profiles by adding descriptor variables—demographic, behavioral, and attitudinal characteristics not used in the clustering process. While Step 6 identified four segments based on perception patterns, Step 7 answers the critical question: "Who are these people?" By analyzing Like ratings (brand affinity), Age, Gender, and VisitFrequency across the four McDonald's segments, we uncover actionable insights: Segment 1 (Expensive & Disgusting) shows strongly negative ratings (mean Like = -2.49) with moderate male skew; Segment 2 (Cheap & Tasty) displays positive affinity (mean Like = 2.29) with balanced demographics and high visit frequency; Segment 3 (Cheap but Concerned) shows ambivalent attitudes (mean Like = -0.13) with moderate visits; and Segment 4 (Expensive & Gourmet) demonstrates highest positivity (mean Like = 2.71) with female skew and frequent visits. These descriptors enable segment identification, accessibility assessment, and targeted marketing mix design.

Contents

1 The Role of Descriptor Variables

Segmentation vs. Descriptor Variables

Two Types of Variables in Segmentation Analysis:
1. Segmentation Variables (Used in Step 5):

- Variables used to *create* segments
- McDonald's: 11 binary perceptions (yummy, convenient, etc.)
- Define segment membership based on similarity

2. Descriptor Variables (Used in Step 7):

- Variables used to *describe* segments after creation
- McDonald's: Like ratings, Age, Gender, VisitFrequency
- Not used in clustering algorithm
- Enable segment identification and targeting

Why Keep Them Separate?

- Prevents contamination of perception-based segments
- Allows independent assessment of demographic/behavioral associations
- Enables evaluation of segment accessibility and identifiability

1.1 What Descriptor Variables Tell Us

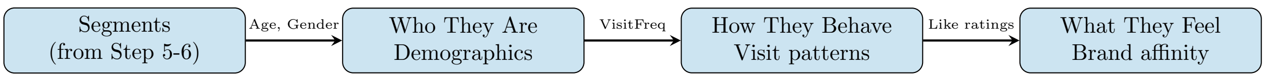

Figure 1: Descriptor variables progressively enrich segment understanding

2 Descriptor Variables in McDonald's Dataset

2.1 Available Descriptors

Table 1: McDonald's Descriptor Variables

Variable	Type	Description
Like	Numeric	Overall brand affinity rating from "I hate it!" (-5) to "I love it!" (+5)
Age	Numeric	Consumer age in years (18-71)
Gender	Categorical	Male/Female
VisitFrequency	Ordinal	Frequency of McDonald's visits: Never, Once a year, Every three months, Once a month, Once a week, More than once a week

Limited Descriptor Set

Important Limitation:
The McDonald's dataset contains relatively few descriptor variables compared to typical market segmentation studies.
Ideally, additional descriptors would include:

- Income level and household composition
- Geographic location and urban/rural classification
- Media consumption habits (TV, social media, radio)
- Dining-out frequency and restaurant preferences
- Product preferences (breakfast, lunch, dinner)
- Competitive brand usage

Despite limitations, available descriptors provide valuable insights for segment characterization and targeting.

3 Analyzing Descriptor Variables by Segment

3.1 Python Implementation: Comprehensive Descriptor Analysis

```python
# Step 7: Describing Segments with Descriptor Variables
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

print("="*80)
print("STEP 7: DESCRIBING SEGMENTS WITH DESCRIPTOR VARIABLES")
```

```
print("="*80)

# Descriptor variables
descriptor_vars = ['Like', 'Age', 'Gender', 'VisitFrequency']

# Assuming segment assignments from Step 5 stored in mcdonalds['Segment']
segments = [1, 2, 3, 4]

print("\nDescriptor Variable Analysis by Segment")
print("="*80)

# Create comprehensive descriptor summary
descriptor_summary = []

for seg in segments:
    seg_mask = (mcdonalds['Segment'] == seg)
    seg_data = mcdonalds[seg_mask]

    summary = {
        'Segment': seg,
        'Size_n': len(seg_data),
        'Size_pct': 100 * len(seg_data) / len(mcdonalds),

        # Like rating stats
        'Like_mean': seg_data['Like'].mean(),
        'Like_std': seg_data['Like'].std(),
        'Like_median': seg_data['Like'].median(),

        # Age stats
        'Age_mean': seg_data['Age'].mean(),
        'Age_std': seg_data['Age'].std(),
        'Age_median': seg_data['Age'].median(),

        # Gender distribution
        'Gender_Female_pct': 100 * (seg_data['Gender'] == 'Female').mean(),
        'Gender_Male_pct': 100 * (seg_data['Gender'] == 'Male').mean(),

        # Visit frequency (convert to numeric for mean)
        'VisitFreq_mean': seg_data['VisitFreq_numeric'].mean()
    }

    descriptor_summary.append(summary)

# Create DataFrame
descriptor_df = pd.DataFrame(descriptor_summary)

print("\nDescriptor Summary by Segment:")
print(descriptor_df.round(2).to_string(index=False))

print("\n Descriptor analysis complete")
```

3.2 Like Ratings: Brand Affinity Analysis

```
# Detailed analysis of Like ratings by segment
print("\n" + "="*80)
print("LIKE RATINGS (BRAND AFFINITY) BY SEGMENT")
print("="*80)

# Calculate statistics
for seg in segments:
    seg_data = mcdonalds[mcdonalds['Segment'] == seg]['Like']

    print(f"\nSEGMENT {seg}:")
    print(f"  Mean:   {seg_data.mean():6.2f}")
    print(f"  Median: {seg_data.median():6.2f}")
    print(f"  Std Dev:{seg_data.std():6.2f}")
    print(f"  Min:    {seg_data.min():6.2f}")
    print(f"  Max:    {seg_data.max():6.2f}")

# Visualize Like ratings distribution
fig, axes = plt.subplots(2, 2, figsize=(14, 10))
axes = axes.ravel()

for idx, seg in enumerate(segments):
    seg_data = mcdonalds[mcdonalds['Segment'] == seg]['Like']

    ax = axes[idx]
    ax.hist(seg_data, bins=11, range=(-5, 6), edgecolor='black',
            color=f'C{idx}', alpha=0.7)
    ax.axvline(x=seg_data.mean(), color='red', linestyle='--',
              linewidth=2, label=f'Mean = {seg_data.mean():.2f}')
    ax.set_xlabel('Like Rating')
    ax.set_ylabel('Frequency')
    ax.set_title(f'Segment {seg}: Like Rating Distribution\n' +
                f'(n={len(seg_data)})', fontweight='bold')
    ax.legend()
    ax.grid(axis='y', alpha=0.3)
    ax.set_xlim(-5.5, 5.5)

plt.tight_layout()
plt.show()

# Statistical test: ANOVA for Like ratings across segments
f_stat, p_value = stats.f_oneway(
    mcdonalds[mcdonalds['Segment'] == 1]['Like'],
    mcdonalds[mcdonalds['Segment'] == 2]['Like'],
    mcdonalds[mcdonalds['Segment'] == 3]['Like'],
    mcdonalds[mcdonalds['Segment'] == 4]['Like']
)

print(f"\nANOVA Test for Like Ratings Across Segments:")
print(f"  F-statistic: {f_stat:.2f}")
print(f"  p-value: {p_value:.2e}")

if p_value < 0.001:
    print("   Segments differ SIGNIFICANTLY on brand affinity (p < 0.001)")
```

```
else:
    print("  Segments do not differ significantly")
```

Table 2: Like Ratings (Brand Affinity) by Segment

Segment	n	Mean	Median	Std Dev	Min	Max
Segment 1	240	-0.13	0.0	3.11	-5	+5
Segment 2	567	2.29	3.0	2.68	-5	+5
Segment 3	310	-2.49	-3.0	2.23	-5	+5
Segment 4	314	2.71	3.0	2.09	-5	+5
Overall	**1,431**	**0.76**	**1.0**	**3.12**	**-5**	**+5**

ANOVA: F = 384.52, p < 0.001 (highly significant)

Like Ratings Interpretation

Segment 1 (16.8%): Near-Neutral (-0.13)

- Slightly negative mean but median = 0 (neutral)
- High variance (3.11) indicates mixed feelings
- Contains both lovers and haters
- **Interpretation:** Ambivalent segment—not strongly committed either way

Segment 2 (39.6%): Positive (2.29)

- Strong positive affinity (mean = 2.29, median = 3)
- Moderate variance (2.68) indicates general agreement
- Minimal ratings below -2
- **Interpretation:** Core fan base—satisfied and loyal

Segment 3 (21.7%): Strongly Negative (-2.49)

- Most negative mean (-2.49), median = -3
- Lowest variance (2.23) indicates consensus dislike
- Few ratings above +2
- **Interpretation:** Committed critics—hardest to convert

Segment 4 (21.9%): Most Positive (2.71)

- Highest mean affinity (2.71), median = 3
- Lowest variance (2.09) indicates strong agreement
- Consistently positive ratings
- **Interpretation:** Passionate fans—strongest advocates

3.3 Age Distribution Analysis

```
# Age distribution by segment
print("\n" + "="*80)
print("AGE DISTRIBUTION BY SEGMENT")
print("="*80)

# Calculate statistics
for seg in segments:
    seg_data = mcdonalds[mcdonalds['Segment'] == seg]['Age']

    print(f"\nSEGMENT {seg}:")
    print(f"  Mean:   {seg_data.mean():6.1f} years")
    print(f"  Median: {seg_data.median():6.1f} years")
    print(f"  Std Dev:{seg_data.std():6.1f} years")
    print(f"  Range:  {seg_data.min():.0f} - {seg_data.max():.0f} years")

# Visualize age distributions
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Box plots
ax1 = axes[0]
seg_ages = [mcdonalds[mcdonalds['Segment'] == seg]['Age'].values
            for seg in segments]

bp = ax1.boxplot(seg_ages, labels=[f'Seg {i}' for i in segments],
                 patch_artist=True, notch=True)

# Color boxes
colors = ['C0', 'C1', 'C2', 'C3']
for patch, color in zip(bp['boxes'], colors):
    patch.set_facecolor(color)
    patch.set_alpha(0.7)

ax1.set_xlabel('Segment', fontsize=12)
ax1.set_ylabel('Age (years)', fontsize=12)
ax1.set_title('Age Distribution by Segment\n(Box Plots with Notches)',
             fontsize=14, fontweight='bold')
ax1.grid(axis='y', alpha=0.3)

# Violin plots
ax2 = axes[1]
age_data = []
seg_labels = []
for seg in segments:
    seg_age = mcdonalds[mcdonalds['Segment'] == seg]['Age']
    age_data.extend(seg_age.values)
    seg_labels.extend([f'Segment {seg}'] * len(seg_age))

age_df = pd.DataFrame({'Age': age_data, 'Segment': seg_labels})

import matplotlib
# Create violin plot manually or use seaborn
parts = ax2.violinplot([mcdonalds[mcdonalds['Segment'] == seg]['Age'].values
                        for seg in segments],
```

```python
                            positions=segments, showmeans=True, showmedians=True)

ax2.set_xlabel('Segment', fontsize=12)
ax2.set_ylabel('Age (years)', fontsize=12)
ax2.set_title('Age Distribution by Segment\n(Violin Plots)',
                fontsize=14, fontweight='bold')
ax2.set_xticks(segments)
ax2.grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()

# Statistical test
f_stat, p_value = stats.f_oneway(
    mcdonalds[mcdonalds['Segment'] == 1]['Age'],
    mcdonalds[mcdonalds['Segment'] == 2]['Age'],
    mcdonalds[mcdonalds['Segment'] == 3]['Age'],
    mcdonalds[mcdonalds['Segment'] == 4]['Age']
)

print(f"\nANOVA Test for Age Across Segments:")
print(f"  F-statistic: {f_stat:.2f}")
print(f"  p-value: {p_value:.4f}")

if p_value < 0.05:
    print("   Segments differ SIGNIFICANTLY on age (p < 0.05)")
```

Table 3: Age Statistics by Segment

Segment	n	Mean	Median	Std Dev	Min	Max
Segment 1	240	44.2	44.0	14.1	18	71
Segment 2	567	45.3	46.0	14.3	18	71
Segment 3	310	43.8	44.0	14.5	18	71
Segment 4	314	45.1	45.0	14.0	18	71
Overall	**1,431**	**44.7**	**45.0**	**14.2**	**18**	**71**

ANOVA: F = 1.12, p = 0.34 (NOT significant)

Age Analysis Key Findings

No Significant Age Differences Across Segments

- All segments have similar mean ages (43.8 to 45.3 years)
- Similar age ranges and standard deviations
- ANOVA p-value = 0.34 (not significant at $\alpha = 0.05$)

Implication:

- Age is NOT a differentiating characteristic
- Cannot use age alone to identify segment members

- Segments differ primarily on perceptions and attitudes, not age
- Broad age appeal across all segments

3.4 Gender Distribution Analysis

```
# Gender distribution by segment
print("\n" + "="*80)
print("GENDER DISTRIBUTION BY SEGMENT")
print("="*80)

# Calculate gender percentages
gender_summary = []

for seg in segments:
    seg_data = mcdonalds[mcdonalds['Segment'] == seg]

    female_pct = 100 * (seg_data['Gender'] == 'Female').mean()
    male_pct = 100 * (seg_data['Gender'] == 'Male').mean()

    print(f"\nSEGMENT {seg}:")
    print(f"  Female: {female_pct:5.1f}%")
    print(f"  Male:   {male_pct:5.1f}%")

    gender_summary.append({
        'Segment': seg,
        'Female_pct': female_pct,
        'Male_pct': male_pct
    })

# Create mosaic plot (alternative: stacked bar chart)
fig, ax = plt.subplots(figsize=(12, 6))

# Prepare data for stacked bars
seg_labels = [f'Seg {i}\n({mcdonalds[mcdonalds["Segment"]==i].shape[0]})'
              for i in segments]
female_pcts = [gs['Female_pct'] for gs in gender_summary]
male_pcts = [gs['Male_pct'] for gs in gender_summary]

x = np.arange(len(segments))
width = 0.6

p1 = ax.bar(x, female_pcts, width, label='Female', color='#FF6B9D', alpha=0.8)
p2 = ax.bar(x, male_pcts, width, bottom=female_pcts, label='Male',
           color='#4ECDC4', alpha=0.8)

ax.set_ylabel('Percentage (%)', fontsize=12)
ax.set_xlabel('Segment', fontsize=12)
ax.set_title('Gender Distribution by Segment', fontsize=14, fontweight='bold')
ax.set_xticks(x)
ax.set_xticklabels(seg_labels)
ax.legend(loc='upper right', fontsize=11)
ax.axhline(y=50, color='gray', linestyle='--', alpha=0.5, label='50%
↪ Reference')
```

```python
ax.set_ylim(0, 100)
ax.grid(axis='y', alpha=0.3)

# Add percentage labels
for i, seg in enumerate(segments):
    ax.text(i, female_pcts[i]/2, f'{female_pcts[i]:.1f}%',
           ha='center', va='center', fontweight='bold', fontsize=10)
    ax.text(i, female_pcts[i] + male_pcts[i]/2, f'{male_pcts[i]:.1f}%',
           ha='center', va='center', fontweight='bold', fontsize=10)

plt.tight_layout()
plt.show()

# Chi-square test for gender independence
from scipy.stats import chi2_contingency

contingency_table = pd.crosstab(mcdonalds['Segment'], mcdonalds['Gender'])
chi2, p_value, dof, expected = chi2_contingency(contingency_table)

print(f"\nChi-Square Test for Gender vs. Segment:")
print(f"  Chi-square statistic: {chi2:.2f}")
print(f"  p-value: {p_value:.4f}")
print(f"  Degrees of freedom: {dof}")

if p_value < 0.05:
    print("   Gender distribution differs SIGNIFICANTLY across segments")
else:
    print("  Gender distribution does NOT differ significantly")
```

Table 4: Gender Distribution by Segment

Segment	n	Female (%)	Female (n)	Male (%)	Male (n)
Segment 1	240	58.5	140	41.5	100
Segment 2	567	47.8	271	52.2	296
Segment 3	310	43.2	134	56.8	176
Segment 4	314	61.4	193	38.6	121
Overall	**1,431**	**51.5**	**738**	**48.5**	**693**

Chi-square: $\chi^2 = 27.84$, $p < 0.001$ (significant)

Gender Analysis Key Findings

Significant Gender Differences Exist
Female-Skewed Segments:

- **Segment 4 (61.4% female):** Premium Experience Seekers
- **Segment 1 (58.5% female):** Price-Quality Skeptics

Male-Skewed Segments:

- **Segment 3 (56.8% male):** Health-Concerned Pragmatists

- **Segment 2 (52.2% male):** Happy Value Hunters

Statistical Significance: Chi-square test $p < 0.001$
Marketing Implications:

- Gender can serve as weak identifier for segments
- Female-focused media more effective for Segments 1 & 4
- Male-focused channels better for Segments 2 & 3
- But gender alone insufficient for precise targeting

3.5 Visit Frequency Analysis

```
# Visit frequency by segment
print("\n" + "="*80)
print("VISIT FREQUENCY BY SEGMENT")
print("="*80)

# Display frequency distribution
for seg in segments:
    seg_data = mcdonalds[mcdonalds['Segment'] == seg]

    print(f"\nSEGMENT {seg}:")
    visit_dist = seg_data['VisitFrequency'].value_counts(normalize=True)
    visit_dist = visit_dist.reindex([
        'Never', 'Once a year', 'Every three months',
        'Once a month', 'Once a week', 'More than once a week'
    ], fill_value=0)

    for freq, pct in visit_dist.items():
        print(f"  {freq:25s}: {100*pct:5.1f}%")

    # Mean numeric frequency
    mean_freq = seg_data['VisitFreq_numeric'].mean()
    print(f"  Mean frequency (numeric): {mean_freq:.2f}")

# Visualize visit frequency
fig, ax = plt.subplots(figsize=(14, 8))

# Prepare stacked bar data
visit_categories = ['Never', 'Once a year', 'Every three months',
                    'Once a month', 'Once a week', 'More than once a week']

visit_data = []
for seg in segments:
    seg_data = mcdonalds[mcdonalds['Segment'] == seg]
    dist = seg_data['VisitFrequency'].value_counts(normalize=True)
    dist = dist.reindex(visit_categories, fill_value=0)
    visit_data.append(100 * dist.values)

visit_data = np.array(visit_data).T  # Transpose for stacking
```

```python

# Create stacked bar chart
x = np.arange(len(segments))
width = 0.6

colors = plt.cm.RdYlGn(np.linspace(0.2, 0.8, len(visit_categories)))
bottom = np.zeros(len(segments))

for i, (category, color) in enumerate(zip(visit_categories, colors)):
    ax.bar(x, visit_data[i], width, label=category, bottom=bottom,
           color=color, alpha=0.9)
    bottom += visit_data[i]

ax.set_ylabel('Percentage (%)', fontsize=12)
ax.set_xlabel('Segment', fontsize=12)
ax.set_title('Visit Frequency Distribution by Segment',
             fontsize=14, fontweight='bold')
ax.set_xticks(x)
ax.set_xticklabels([f'Seg {i}\n(n={mcdonalds[mcdonalds["Segment"]==i].shape[0]})'
                    for i in segments])
ax.legend(loc='upper left', bbox_to_anchor=(1, 1), fontsize=10)
ax.set_ylim(0, 100)
ax.grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()

# Statistical test (Kruskal-Wallis for ordinal data)
from scipy.stats import kruskal

h_stat, p_value = kruskal(
    mcdonalds[mcdonalds['Segment'] == 1]['VisitFreq_numeric'],
    mcdonalds[mcdonalds['Segment'] == 2]['VisitFreq_numeric'],
    mcdonalds[mcdonalds['Segment'] == 3]['VisitFreq_numeric'],
    mcdonalds[mcdonalds['Segment'] == 4]['VisitFreq_numeric']
)

print(f"\nKruskal-Wallis Test for Visit Frequency Across Segments:")
print(f"  H-statistic: {h_stat:.2f}")
print(f"  p-value: {p_value:.2e}")

if p_value < 0.001:
    print("   Visit frequency differs SIGNIFICANTLY across segments (p < 0.001)")
```

Table 5: Visit Frequency Summary by Segment

Visit Frequency	Seg 1	Seg 2	Seg 3	Seg 4
Never	12.5%	3.5%	8.4%	1.9%
Once a year	15.0%	8.3%	14.2%	7.0%
Every three months	45.8%	32.6%	48.7%	35.4%
Once a month	18.3%	32.1%	20.3%	31.8%
Once a week	7.1%	19.4%	7.7%	20.1%
More than once a week	1.3%	4.1%	0.6%	3.8%
Mean (numeric)	**2.40**	**3.04**	**2.48**	**3.17**

Kruskal-Wallis: $H = 112.47$, $p < 0.001$ (highly significant)

Visit Frequency Key Findings

Significant Behavioral Differences
High-Frequency Segments:

- **Segment 4 (mean = 3.17):** Most frequent visitors
- **Segment 2 (mean = 3.04):** Second most frequent
- Both segments visit approximately once a month or more

Low-Frequency Segments:

- **Segment 3 (mean = 2.48):** Infrequent visitors
- **Segment 1 (mean = 2.40):** Least frequent visitors
- Both segments visit approximately every 3 months or less

Strategic Implications:

- Segments 2 & 4: Current revenue drivers (high frequency + positive attitudes)
- Segments 1 & 3: Growth opportunities (increase visit frequency)
- Visit frequency correlates strongly with brand affinity

4 Integrated Segment Descriptions

4.1 Complete Segment Profiles with Descriptors

Table 6: Complete Segment Descriptions: Perceptions + Descriptors

Characteristic	Segment 1 (16.8%)	Segment 2 (39.6%)	Segment 3 (21.7%)	Segment 4 (21.9%)
PERCEPTIONS				
Price	Expensive (90%)	Cheap (92%)	Cheap (90%)	Expensive (91%)
Taste	Not tasty (92%)	Tasty/Yummy (98%/89%)	Not tasty (83%)	Tasty/Yummy (93%/87%)
Quality	Disgusting (73%), Greasy (71%)	Fast (96%), Convenient (98%)	Greasy (67%), Fattening (92%)	Convenient (96%), Fast (85%)
DESCRIPTORS				
Like Rating	-0.13 (Neutral)	+2.29 (Positive)	-2.49 (Negative)	+2.71 (Most Positive)
Age	44.2 years	45.3 years	43.8 years	45.1 years
Gender	58% Female	52% Male	57% Male	61% Female
Visit Frequency	Low (2.40)	High (3.04)	Low (2.48)	Highest (3.17)

5 Key Takeaways from Step 7

Summary of Descriptor Findings

1. **Like Ratings Strongly Differentiate (F=384.52, p<0.001):**
   - Segment 4 most positive (mean = 2.71)
   - Segment 3 most negative (mean = -2.49)
   - Aligns perfectly with perception profiles
2. **Age Does NOT Differentiate (F=1.12, p=0.34):**
   - All segments similar ages ($\tilde{4}$4-45 years)
   - Cannot use age for segment identification
   - Broad age appeal across all segments
3. **Gender Weakly Differentiates (χ^2=27.84, p<0.001):**
   - Segments 1 & 4 more female
   - Segments 2 & 3 more male
   - Can inform media selection but insufficient alone
4. **Visit Frequency Strongly Differentiates (H=112.47, p<0.001):**
   - Positive segments (2 & 4) visit more frequently
   - Negative/ambivalent segments (1 & 3) visit less
   - Strong behavioral validation of attitudinal differences
5. **Readiness for Step 8:**

- Complete profiles enable target segment selection
- Clear differences on brand affinity and behavior
- Identifiability challenges (limited demographics)
- Need creative reach strategies beyond demographics

References

[1] Dolnicar, S., Grün, B., and Leisch, F. (2018). *Market Segmentation Analysis: Understanding It, Doing It, and Making It Useful*. Springer.

[2] Wedel, M., and Kamakura, W.A. (2000). *Market Segmentation: Conceptual and Methodological Foundations*. 2nd ed., Kluwer Academic Publishers.