Market Segmentation Analysis – McDonald's Fast Food Case Study

Steps Covered in This Report:
This PDF was compiled and prepared by **Zeba Khanam**, covering the following steps:

- **Step 1, Step 2, Step 3**
- **Step 8 – Selecting the Target Segment**
- **Step 9 – Customising the Marketing Mix**

Additional step contributions included from team members:

- **Narsimha Vemula – Step 4 & Step 5**
- **Samiksha Kamble – Step 6 & Step 7**

Colab Notebook Link: Click Here **Zeba khanam**.

Step 1: Deciding (Not) to Segment

In this step, McDonald's must decide whether it wants to treat the entire market as one or divide it into smaller, meaningful segments.

- If they don't segment: One strategy for all customers.
- If they do segment: They can tailor their products and messages to different customer needs.

Why segment?
Because customers differ in their needs, preferences, and behaviors. Even a big brand like McDonald's can benefit from targeting smaller groups more effectively.

Step 2: Specifying the Ideal Target Segment

To identify the best segment, McDonald's uses two sets of criteria:

1. Knock-out Criteria:

These are basic rules. A good segment must be:

- Homogeneous (members are similar)

- Distinct from others
- Big enough
- Match the brand’s strengths
- Easy to identify
- Easy to reach through ads or channels

2. Attractiveness Criteria:

- Likes McDonald’s
- Eats at McDonald’s often
- Open to fast food
- Can be influenced by marketing

Step 3: Collecting Data

McDonald’s conducted a survey of 1453 Australian adults to know how they perceive the brand.

They asked:

- 11 attribute-based questions (e.g., Is McDonald’s “yummy”, “fast”, “expensive”?)
- Demographic data like age and gender
- Visit frequency and whether they like McDonald’s

Format of data:

- Most responses were YES/NO
- Like was rated on a scale from -5 (hate it) to +5 (love it)

This step gave the raw data needed for segmentation analysis in the next steps.

Step 4: Exploring Data

Basic exploration was done to understand:

- Distribution of variables (e.g., gender count, visit frequency)
- Conversion of YES/NO to binary format
- Presence of missing values (handled or dropped)
- Use of PCA (Principal Component Analysis) to visualize patterns among customer perceptions

The aim was to prepare clean and structured data for clustering.

Step 5: Extracting Segments

Segmentation was done using the **KMeans algorithm** for k = 2 to 8.

Key steps:

- **Scree Plot** was used to analyze how much variation is explained by each k
- **Stability Analysis** was done (bootstrap and replication testing)
- **4-segment solution** was found to be the best — stable and meaningful

Different types of clustering were also explored in the PDF (e.g., finite mixtures, regression models), but KMeans was found practical and effective for implementation in Python.

Step 6: Profiling Segments

Profiling is essential in data-driven segmentation, not commonsense segmentation.

Goal is to understand and describe each segment and compare them for strategic insights.

Profiling process: Describe segments individually.

Compare segments against each other and the overall sample.

Challenges:

- Users struggle to interpret segmentation results.
- Oversimplified summaries → too trivial.
- Detailed tables → too complex

- Accurate profiling leads to better marketing decisions.
- Segment Profiling with Visualisations
    - Visualisations:

        - Simplify complex data and enhance interpretation.
        - Help detect marker variables (defining characteristics).
        - Improve communication to non-technical stakeholders.

- Segment Profile Plots: Show how each segment differs from the average.
    - Variables can be reordered using hierarchical clustering for clarity

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Step 7: Describing Segments

- Segment profiling uses segmentation variables; segment describing uses extra variables (descriptor variables like age, gender, income) to better understand segments and tailor marketing strategies.
- Descriptor variables add depth to segmentation.

- Visual tools (like charts) make segment comparisons clearer and easier than tables. They help avoid reading too much into small differences.
- Visualizations (e.g., mosaic plots) highlight meaningful differences and patterns.

- Use cross-tabs and visual tools like stacked bar charts and mosaic plots to compare categorical descriptors (e.g., gender or income) across segments.

- Metric Descriptor Variables - Numerical descriptors (like age or moral values) help understand how segments differ in measurable ways.
- Conditional Histograms - Show distributions of numerical variables (like age) for each segment separately; useful for exploration but not always easy to compare.
- Parallel Box-and-Whisker Plots - Boxplots show how segments differ in metrics like age or moral values, and they highlight significant differences using confidence intervals and box widths.
- Modified SLSA Plot - Tracks how segments and their traits (like moral obligation) stay stable or change across different segmentation models.
- Boxplots and SLSA are better for comparison than histograms.
- Regression Models

    - Models like linear or logistic regression help predict segment based on descriptors.
    - Logistic regression is used when the outcome is categorical (e.g., which segment).
    - Binary Logistic Regression

- Predicts whether someone is in a specific segment (yes/no) using variables like age or values.

- Uses age and moral obligation to predict if someone is in a particular segment. Results show which traits matter most
.

- Coefficients tell how each variable affects the probability of being in the segment.

- Plots show how age or moral values affect the likelihood of segment membership.

- Multinomial Logistic Regression
  Used when there are more than two segments. Predicts which one a person is likely to belong to.

  - Coefficients tell how descriptors (like age or values) change the odds of belonging to each segment.

  - Tests whether the descriptors as a group are useful predictors.

  - Can predict actual segment or probability of belonging to each one.

- Tree-Based Methods

  Decision trees predict outcomes by splitting data into groups step-by-step.
  - Easy to intepret and handle complex data, but results can change a lot with small data changes.
  - The method of repeatedly splitting data to make groups more similar internally.
  - Trees differ in how they split, choose variables, stop growing, and make predictions.
  - Each split shows how outcomes are distributed; deeper levels give more specific predictions.

  - Multiclass Prediction: Trees can predict multiple segments (not just yes/no) at once

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Step 8 – Selecting the Target Segment

In this step, our goal was to identify the most attractive segment from the four segments generated through KMeans clustering.

Segment Evaluation Process:

- We created a summary table with the average VisitFrequency, Like score, and percentage of female customers for each segment using Python.
- A **bubble plot** was created where:
    - X-axis = Mean Visit Frequency
    - Y-axis = Mean Like Score
    - Bubble size = % Female Customers
    - Each bubble represented a segment

This visualization helped us quickly identify which segments were most favorable based on customer preferences and behavior.

Insights:

- **Segment 3** stood out with:
    - High liking scores
    - Frequent visits to McDonald's
    - Mostly young users
- Segment 3 was selected as the target segment for further marketing focus.

Decision Tree Analysis:

- We built a Decision Tree classifier using:
    - Input Features: Like, Visit Frequency, Age, Gender
    - Target: Whether a person belongs to Segment 3 or not
- The tree clearly showed that people who:
    - Like McDonald's,
    - Are young,
    - Visit more than once a month,
    - Are more likely to belong to Segment 3.

This confirmed our decision to choose Segment 3 for targeting.

Step 9 – Customising the Marketing Mix for Segment 3

Based on the profiling, Segment 3 consists of young customers who enjoy McDonald's food and visit frequently but find it expensive.

Marketing Strategy Using 4Ps:

Product:

Launch a **McDonald's SUPERBUDGET** menu designed with tasty but low-cost items.

This line must be clearly different from premium products to avoid internal competition.

Price:

Keep meal combos in the ₹79–₹99 range.

Offer loyalty points, discounts for app orders, or student-based pricing.

Place:

Use existing McDonald's outlets.

Introduce a dedicated counter or lane for budget menu orders.

Promotion:

Focus on platforms like Instagram, YouTube, and Snapchat.

Use college influencers and promote through youth-oriented content.

Messages should focus on affordability, fun, and convenience.

Objective:

Retain young, loyal customers by addressing price concerns. As they grow older and earn more, they may transition to regular offerings, increasing lifetime value.