**MARKET SEGMENTATION ANALYSIS**

*Understanding it, doing it, and making it useful*

## **Chapter 1: Market Segmentation**

### **🔹 1.1 Strategic and Tactical Marketing**

When companies think about marketing, they usually break it into two parts: **strategic** and **tactical**.

* **Strategic marketing** is the big-picture thinking—like choosing which customers to target or how the product should be positioned in their minds.
* **Tactical marketing** is more hands-on—things like advertising, pricing, promotions, and distribution.

The problem is, while companies often jump straight into tactical decisions, they sometimes skip the strategic part. But without a strong strategy, even the best marketing tactics can fail. That’s why market segmentation is crucial—it connects both strategy and tactics. It helps define who the customer is, which in turn guides what we say to them and how.

### **🔹 1.2 Definitions of Market Segmentation**

There are many ways to define market segmentation, but they all come down to this:

**It’s the process of dividing a broad consumer or business market into sub-groups of consumers (called segments) based on shared characteristics.**

These shared characteristics can be **demographic**, **geographic**, **psychographic**, or **behavioral**. The goal is to group similar people together so that companies can tailor their strategies to better serve each group.

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### **🔹 1.3 The Benefits of Market Segmentation**

Segmentation makes marketing smarter and more efficient. Some benefits include

* **Better understanding of customer needs.**
* **More targeted and relevant marketing messages.**
* **Improved product design** because products are based on what specific segments actually want.
* **Competitive advantage**—if you understand your customers better, you can serve them better.
* **Resource efficiency**—you don’t waste time and money marketing to people who won’t respond.

### **🔹 1.4 The Costs of Market Segmentation**

Of course, segmentation isn’t free. There are trade-offs:

* It adds **complexity**—instead of one campaign or product, now you have to manage many.
* It takes more **time and effort** to analyze customer data and set up different strategies.
* **Organizational resistance** is common—some teams may not want to change how they’ve always done things.
* There’s also a risk that if segmentation isn’t done properly, it could lead to poor decisions.

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## **Chapter 2: Market Segmentation Analysis**

### **🔹 2.1 The Layers of Market Segmentation Analysis**

Think of market segmentation analysis like peeling an onion—it has layers:

1. **Strategic Layer**: First, the company decides *why* it wants to segment the market and what the ideal customer looks like.
2. **Analytical Layer**: Then the data is collected, cleaned, and analyzed using statistical techniques to find patterns.
3. **Implementation Layer**: Finally, the company acts on the results—designing specific campaigns or offers for each segment.

Each of these layers is important, and if one is skipped, the whole strategy can fall apart.

### **🔹 2.2 Approaches to Market Segmentation Analysis**

#### **2.2.1 Based on Organizational Constraints**

Not every company can afford or execute complex segmentation. So segmentation strategies are often shaped by constraints like

* Budget
* Staff capabilities
* Available data
* Software tools

The more constrained a company is, the simpler their segmentation approach needs to be. Some may use basic customer surveys, while others can go for full-on predictive modeling.

#### **2.2.2 Based on the Choice of Segmentation Variables**

This is all about what data you're using to group people. Common approaches:

* **A priori** segmentation: Use known variables like age or gender to group people.
* **Post hoc** segmentation: Let statistical methods find natural clusters based on lots of variables (e.g., K-means clustering on behaviors).

Choosing the right variables is critical. If you use the wrong ones, the segments you find won’t be helpful in real life.

### **🔹 2.3 Data Structure and Data-Driven Segmentation**

Data quality plays a huge role here. Messy or incomplete data can ruin segmentation analysis. Good data should be:

* Clean (no missing or strange values)
* Relevant (measuring things that matter)
* Sufficient (enough size and variety)

The authors emphasize the power of **data-driven segmentation**, where algorithms find patterns without human bias. But even here, human judgment is still needed to interpret and apply the findings.

### **🔹 2.4 Market Segmentation Analysis Step-by-Step**

This is the heart of the book. The authors introduce their **10-step framework** for segmentation analysis, which the rest of the book explores in detail. The steps are:

1. Decide (not) to segment
2. Specify the ideal target segment
3. Collect data
4. Explore the data
5. Extract segments
6. Profile segments
7. Describe segments
8. Select target segment(s)
9. Customize the marketing mix
10. Evaluate and monitor

## **Chapter 3: Step 1 — Deciding (Not) to Segment**

### **🔹 3.1 Implications of Committing to Market Segmentation**

So, before jumping into segmentation, the first step is to **ask whether it’s even necessary**. Just because we *can* segment doesn’t mean we *should*.

Segmentation works best when:

* The market is **diverse**—different people have different preferences.
* The product or service allows **flexibility** to be marketed differently to different groups.
* The organization is ready to **act on the findings**—it takes time, effort, and money to implement segmented strategies.

Once a business commits to segmentation, it must:

* Think more **strategically** about marketing.
* Possibly redesign products, services, and messaging to fit each group.
* Accept that **internal change** may be needed, especially in teams or decision-making structures.

### **🔹 3.2 Implementation Barriers**

While segmentation is a powerful tool, it's not always easy to pull off. Here are the common **obstacles**:

* **Cost**: Collecting and analyzing detailed data can be expensive.
* **Complexity**: More segments = more campaigns, messages, and logistics.
* **Data Limitations**: Sometimes we simply don’t have enough data or the right kind.
* **Organizational Resistance**: Teams may not like changing how they’ve always worked.
* **Execution Gap**: Even if analysis is done, the marketing team might not use it effectively.

## **Chapter 4: Step 2 — Specifying the Ideal Target Segment**

This step is about defining what kind of segment you're even looking for. Before diving into analysis, we need to be clear about what makes a segment *worth going after*.

### **🔹 4.1 Segment Evaluation Criteria**

We evaluate segments based on several criteria:

* **Size**: Is the segment big enough to matter?
* **Growth**: Is it expanding or shrinking?
* **Profitability**: Can we make money from it?
* **Accessibility**: Can we reach it with marketing and distribution?
* **Fit**: Does it align with our brand, values, and resources?

The more boxes a segment ticks, the more ideal it is.

### **🔹 4.2 Knock-Out Criteria**

Think of these as automatic deal-breakers. If a segment doesn’t meet them, we don’t pursue it—no matter how tempting.

Examples:

* A segment might be **too small** to justify the cost.
* **Legal barriers** may exist (e.g., age restrictions).
* The segment might need a product that’s **too far** from what we offer.

These criteria help us stay realistic and focused.

### **🔹 4.3 Attractiveness Criteria**

After ruling out non-viable segments, we score the remaining ones based on attractiveness:

* High purchasing power?
* Loyalty potential?
* Low competition?
* Low marketing cost?

We can even create a **scoring system** to rank segments based on these attributes.

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### **🔹 4.4 Implementing a Structured Process**

To avoid bias and guesswork, the book suggests using a **structured framework**:

* List all possible segments.
* Apply knock-out criteria.
* Score remaining segments on attractiveness.
* Use this to **prioritize** which segments to investigate further.

## **Chapter 5: Step 3 — Collecting Data**

### **🔹 5.1 Segmentation Variables**

This part focuses on deciding **what kind of information** we need to collect for effective segmentation. We call these **segmentation variables**, and they can come from four major types:

### **🔹 5.2 Segmentation Criteria**

#### **1. Geographic Segmentation**

* Based on location (country, city, region).
* Useful when local culture or infrastructure affects buying behavior.

#### **2. Socio-Demographic Segmentation**

* Age, gender, income, education, occupation, etc.
* These are easy to collect and often useful, but not always enough on their own.

#### **3. Psychographic Segmentation**

* Looks at values, interests, lifestyle, and opinions.
* Helps us understand *why* people buy—not just *who* they are.

#### **4. Behavioral Segmentation**

* Based on actions: purchase history, brand loyalty, usage patterns, etc.
* Great for creating targeted offers.

The best segmentations often use a **mix** of these variables.

### **🔹 5.3 Data from Survey Studies**

Surveys are one of the most common ways to get segmentation data. Key things to consider:

* **Choosing the right questions**: Make sure they relate directly to segmentation goals.
* **Question formats**: Use consistent scales (e.g., 1 to 5) to keep data clean.
* **Response styles**: Some people always choose the middle or extreme ends—watch out for that.
* **Sample size**: Bigger isn’t always better, but you need enough people to represent each segment.

### **🔹 5.4 Other Data Sources**

Besides surveys, you can also use

* **Internal data**: CRM systems, purchase histories.
* **Experimental data**: A/B tests, conjoint studies.
* These often reveal *real behavior*, which can be more accurate than self-reported survey answers.

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## **Chapter 6: Step 4 — Exploring Data**

### **🔹 6.1 A First Glimpse at the Data**

* Always start by looking at basic stats:  
  + Means
  + Medians
  + Frequencies
* This helps spot obvious issues like **missing values**, **weird outliers**, or **unbalanced categories**.

### **🔹 6.2 Data Cleaning**

Clean data = good results. Here’s what to watch for:

* **Missing values**: Decide whether to drop, fill, or impute.
* **Inconsistent coding**: “Yes” vs “YES” vs “1” – they should all mean the same thing.
* **Outliers**: Extreme values that can skew your results—either fix or exclude them carefully.

### **🔹 6.3 Descriptive Analysis**

This is where we start summarizing the data visually:

* Use **histograms** for numeric values.
* Use **bar charts** for categorical variables.
* This shows us how people answered and where the data clusters.

### **🔹 6.4 Pre-Processing**

Before you feed data into clustering algorithms, it needs to be formatted right.

#### **🔸 Categorical Variables**

* Convert Yes/No into 1/0
* Use one-hot encoding if needed

#### **🔸 Numeric Variables**

* Scale/normalize them if they’re on different units (e.g., income vs age)

### **🔹 6.5 Principal Components Analysis (PCA)**

This is a technique to **reduce the number of variables** while keeping most of the information. It helps.

* Simplify complex data
* Identify hidden patterns
* Improve visualization

## **Chapter 7: Step 5 — Extracting Segments**

### **🔹 7.1 Grouping Consumers**

The main goal is to create **internally similar but externally different** groups. There are two key approaches:

* **Distance-Based Methods** (like K-means): Based on how close observations are in feature space.
* **Model-Based Methods** (like mixture models): Based on how well data fits a statistical model.

### **🔹 7.2 Distance-Based Methods**

#### **7.2.1 Distance Measures**

To measure how “close” people are, we need distance metrics like:

* **Euclidean Distance**: Straight-line distance.
* **Manhattan Distance**: Like walking city blocks.
* **Angle-Based Distance**: Useful for directional similarity.

#### **7.2.2 Hierarchical Clustering**

* Builds a **tree (dendrogram)** of segments from the bottom up.
* Doesn’t need you to pre-decide the number of clusters.
* Methods include:  
  + **Single Linkage** (based on nearest neighbor)
  + **Complete Linkage** (based on furthest neighbor)
  + **Ward’s Method** (minimizes internal variance)

#### **7.2.3 K-Means Clustering**

* Probably the most common technique.
* You tell it how many segments (k) to make.
* It groups people by minimizing within-group variance.

#### **7.2.4 Hybrid Approaches**

* Combine methods—for example, first do K-means, then apply hierarchical clustering to the cluster centers.
* More flexible, often gives better segment separation.

### **🔹 7.3 Model-Based Methods**

Instead of just measuring distance, these use statistical models.

#### **7.3.1 Finite Mixture Models**

* Assume data comes from different statistical distributions.
* Each segment is represented by a component (e.g., a Gaussian).
* Gives **probability-based membership**, not hard assignments.

#### **7.3.2 Mixtures of Regressions**

* Fit a different **regression model** to each segment.
* Useful when relationships differ between groups.

#### **7.3.3 Extensions**

* You can include **covariates**, **different distributions**, and more complex structures.

### **🔹 7.4 Algorithms with Built-In Variable Selection**

These algorithms **choose important variables while clustering**. Examples:

* **Biclustering**: Groups rows and columns at the same time.
* **VSBD (Variable Selection for Binary Data)**: Specifically for yes/no datasets.

### **🔹 7.5 Data Structure Analysis**

Once segments are extracted, we want to check:

* **Stability**: Do similar segments show up in repeated runs?
* **Separation**: Are segments clearly different?
* **Cluster Indices**: Like silhouette score, Dunn index, etc.
* **Gorge Plots**: Visual tools to find the “right” number of segments.

## **Chapter 8: Step 6 — Profiling Segments**

Now that the groups are formed, it’s time to **get to know them**. This step is about identifying what makes each segment unique.

### **🔹 8.1 Identifying Key Characteristics**

Here’s the big idea:

Profiling helps us turn anonymous clusters into **personas** we can understand and target.

We do this by comparing

* Demographics
* Psychographics
* Behavioral traits
* Preferences or attitudes

### **🔹 8.2 Traditional Profiling Approaches**

The classic approach is

* Compute **averages** (mean age, mean satisfaction, etc.)
* Look at **percentages** (e.g., 80% female in Segment 1)
* Highlight **differences** between segments

This works, but it can get boring or overwhelming when there are many variables.

### **🔹 8.3 Segment Profiling with Visualisations**

Visuals make it easier to communicate insights to others.

#### **8.3.1 Identifying Defining Characteristics**

* Use **bar charts**, **boxplots**, or **dot plots**.
* These show which traits stand out in each group.

#### **8.3.2 Assessing Segment Separation**

* Use **PCA plots** to visually check if groups are distinct.
* If the clusters look blurred or overlapping, the segmentation might not be useful.

Link to the Jupyter notebook [McDONALDS\_ANALYSIS](http://localhost:8888/notebooks/McDONALADS_ANALYSIS.ipynb)