Case Study: Fast Food(Mc Donald’s)

The purpose of this case study is to illustrate market segmentation analysis using a different empirical data set. The data set was collected for the purpose of comparing the validity of different answer formats in survey research investigating brand image. McDonald's management needs to decide which key features make a market segment attractive to them, and then decide which market segments to focus on and what messages to communicate to them. The target segment must be homogeneous, distinct, large enough to justify a customized marketing mix, matching the strengths of McDonald’s, identifiable and reachable. The data set contains responses from 1453 adult Australian consumers relating to their perceptions of McDonald’s with respect to the following attributes: YUMMY, CONVENIENT, SPICY, FATTENING, GREASY, FAST, CHEAP, TASTY, EXPENSIVE, HEALTHY, and DISGUSTING.

Step 1: Deciding (not) to Segment

McDonald’s can take the position that it caters to the entire market and that there is no need to understand systematic differences across market segments. Alternatively, McDonald’s can take the position that, despite their market power, there is value in investigating systematic heterogeneity among consumers and harvest these differences using a differentiated marketing strategy.

Step 2: Specifying the Ideal Target Segment

McDonald’s management needs to decide which key features make a market segment attractive to them. In terms of knock-out criteria, the target segment or target segments must be homogeneous.In terms of segment attractiveness criteria, the obvious choice would be a segment that has a positive perception of McDonald’s, frequently eats out and likes fast food.They can also learn more about market segments which are currently not fond of McDonald’s; try to understand which perceptions are responsible for this; and attempt to modify those very perceptions.

Step 3: Collecting Data

The data set contains responses from 1453 adult Australian consumers relating to their perceptions of McDonald’s with respect to the following attributes: YUMMY, CONVENIENT, SPICY, FATTENING, GREASY, FAST, CHEAP, TASTY, EXPENSIVE, HEALTHY, and DISGUSTING.

The most important details in this text are the key characteristics of the data set, such as the variable names, sample size, and the first three rows of the data. Additionally, respondents indicated their age, gender, visit frequency, and use of information channels. The first respondent believes McDonald's is not tasty, convenient, fattening, greasy, fast, cheap, not tasty, expensive, not healthy, and not disgusting. The segmentation variables (perception of McDonald's) are verbal, not numeric. To extract numbers, we store the segmentation variables in a separate matrix and convert them from verbal YES/NO to numeric binary. We check that the transformation is correct by inspecting the average value of each transformed segmentation variable

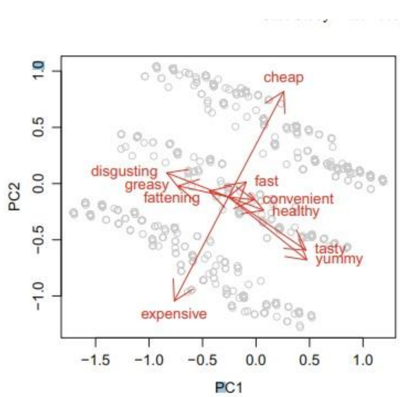
Step 4: Exploring Data

First we extract the first eleven columns from the data set because these columns contain the segmentation variables, and convert the data to a matrix. Then we identify all YES entries in the matrix. This results in a logical matrix with entries TRUE and FALSE. Adding 0 to the logical matrix converts TRUE to 1, and FALSE to 0. We check that we transformed the data correctly by inspecting the average value of each transformed segmentation variable

The average values of transformed binary numeric segmentation variables indicate that 55% of respondents perceive McDonald's as YUMMY, 91% as CONVENIENT, and 9% as SPICY.

Another way of exploring data initially is to compute a principal components analysis, and create a perceptual map. A perceptual map offers initial insights into how attributes are rated by respondents and, importantly, which attributes tend to be rated in the same way.

Principal components analysis is used to create a perceptual map, and the first two components capture 50% of the information contained in the segmentation variables. The factor loadings indicate how the original variables are combined to form principal components. Standard deviations are 0.8, 0.6, 0.4, 0.3, 0.3, 0.3, 0.2, 0.2. Exploring data 273 shows that PC1 PC2 PC3 PC4 PC5 PC6 PC7 yummy, convenient, spicy, fattening, greasy, fast, cheap, tasty, expensive, unhealthy, disgusting, and disgusting are all represented.



Step 5: Extracting Segments

The two segmentation variables with the highest loadings for principal component 2 are CHEAP and EXPENSIVE. The remaining attributes align with positive versus negative perceptions, with FATTENING, DISGUSTING and GREASY in the same direction and FAST, CONVENIENT, HEALTHY, as well as TASTY and YUMMY in the opposite direction. The observations along the EXPENSIVE versus CHEAP axis cluster around three values. Principal components analysis of a fast food data set revealed that some attributes are strongly related to one another and that the price dimension may be critical in differentiating between groups of consumers. Step 5 is where we extract segments using standard k-means analysis, finite mixtures of binary distributions, and finite mixtures of regressions. Results indicate that some attributes are strongly related to one another and that the price dimension may be critical in differentiating between groups of consumers.

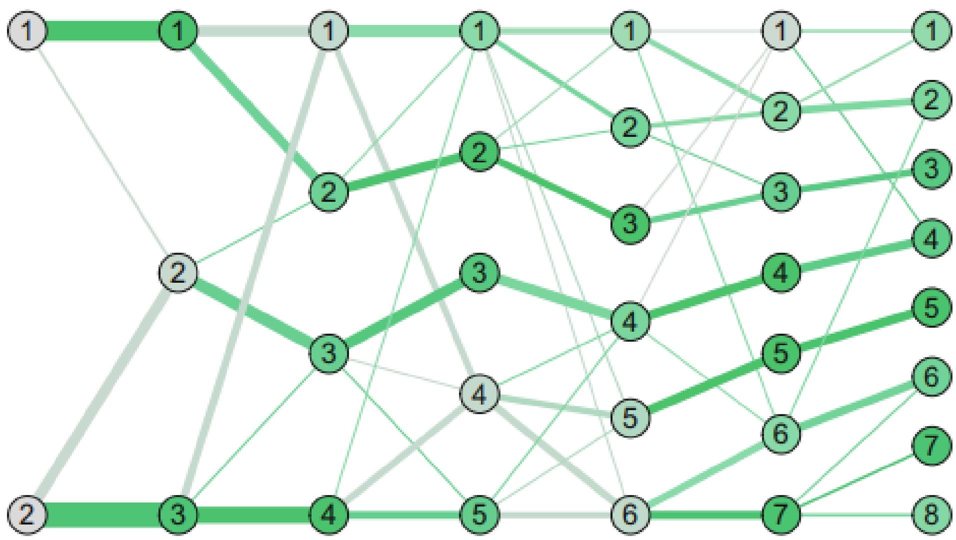


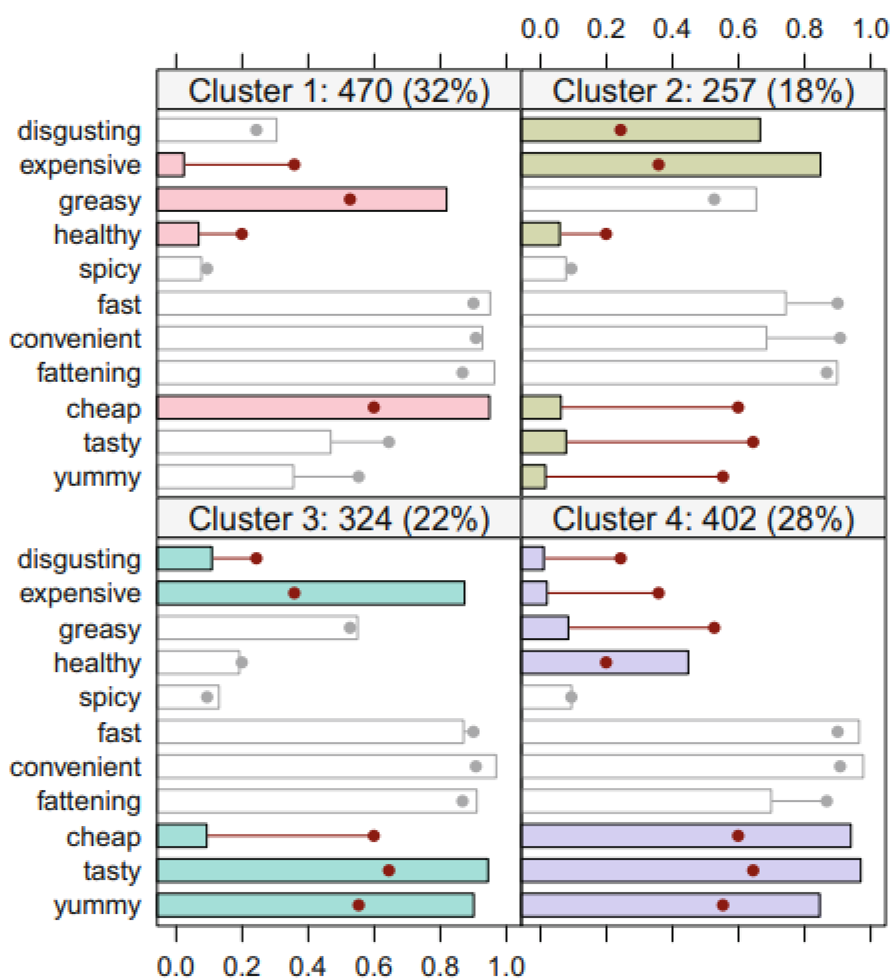
Fig. A.5 Segment level stability across solutions (SLS_A) plot from two to eight segments for the fast food data set

the segment level stability across solutions (SLSA) plot in Fig. A.5 shows that segments 2, 3 and 4 are nearly identical to the corresponding segments in similarity. This is based on a comparison of segmentation solutions with the same number of segments. The four-segment k-means solution for the fast food data set displays high stability across solutions with different numbers of segments. Segment 1 in the four-segment solution draws members from two segments in the three-segment solution and splits up again into two segments contained in the five-segment solution. This highlights that segment 1 may not be a good target segment due to its lack of stability. Global stability assesses the stability of a segmentation solution in its entirety, not investigating the stability of each market segment.

We calculate latent class analysis using a finite mixture of binary distributions. The mixture model maximises the likelihood to extract segments.

Instead of finding market segments of consumers with similar perceptions of McDonald's, it may be interesting to find market segments containing members whose love or hate for McDonald's is driven by similar perceptions. This segmentation approach would enable McDonald's to modify critical perceptions selectively for certain target segments in view of improving love and reducing hate. We extract such market segments using finite mixtures of linear regression models, also called latent class regressions.

Step 6: Profiling Segments



Segment profile plot for the four-segment solution for the fast food data set

McDonald's managers can interpret the diagram which shows four market segments and their size. The names of the segmentation variables (attributes) are written on the left side of the plot. The horizontal lines with the dot at the end indicate the percentage of respondents who associate each perception with McDonald's. Marker variables are coloured differently for each segment and all other variables are grayed out. To understand the market segments, McDonald's managers need to compare the bars for each segment with the horizontal lines and compare bars across segments. The segment separation plot can be customized with additional arguments. The most important details in this text are the use of principal components analysis (PCA) to explore data from a fast food data set. PCA shows that segments 1 and 4 both view McDonald’s as cheap, with members of segment 4 holding positive beliefs and members of segment 1 associating it with negative attributes. Segments 2 and 3 agree that McDonald’s is not cheap, but disagree on other features. At the end of Step 6, McDonald’s managers have a good understanding of the nature of the four market segments, but know little about them.

Segment 1 is the least stable across replications, followed by segments 4 and 2. Segment 3 is the most stable. Latent class analysis is used to extract segments using a finite mixture of binary distributions. R> library("flexmix") R> set.seed(1234) R> MD.m28 - stepFlexmix(MD.x 1, model = FLXMCmvbinary(), k = 2:8, nrep = 10, verbose = FALSE) R> MD.m28 - stepFlexmix(MD.x 1, model = FLXMCmvbinary(), k = 2:8, nrep = 10, verbose = FALSE) R> MD.m28 - stepFlexmix(MD.x 1, model = FLXMCmvbinary(), k = 2:8, nrep = 10, verbose = FALSE) R> MD.m28 - stepFlexmix(MD.x 1, model = FLXMCmvbinary(), k = 2:8, nrep = 10, verbose = FALSE) R> MD.m28 - stepFlexmix(MD.x 1,

The four-component solution and the four-cluster k-means solution are compared using a cross-tabulation. The mixture model draws two thirds of its members from segment 4 of the k-means solution, while the k-means solution draws 191 members from segment 1. This suggests that the two segmentation solutions are similar. The EM algorithm maximizes the log likelihood of two fitted mixture models obtained using two different ways of initialisation. The log-likelihood values for the two solutions are very close, with random initialisations leading to a slightly better result. This gives more confidence that the result is a global optimum or a reasonably close approximation to the global optimum. This segmentation approach would enable McDonald’s to modify critical perceptions selectively for certain target segments in view of improving love and reducing hate.

Latent class regression models are used to measure the degree to which consumers love or hate McDonald's. The dependent variable is measured on an 11-point scale with endpoints labeled I LOVE IT! and I HATE IT! The independent variables are the perceptions of McDonald's. To create a numerical dependent variable, the ordinal variable LIKE is converted to a numeric variable. A model formula is created manually by typing the eleven variable names and separating them by plus signs. R is used to automate the process of collapsing eleven independent variables into a single string separated by plus signs and pasting the dependent variable Like.n to it. The EM algorithm is used to fit a finite mixture of linear regression models with nrep = 10 random starts and k = 2 components. Cluster sizes are 1 2 630 823 and converge after 68 iterations. The dependent variable is not metric, but an ordinal variable with assigned scores with values 5 to +5.

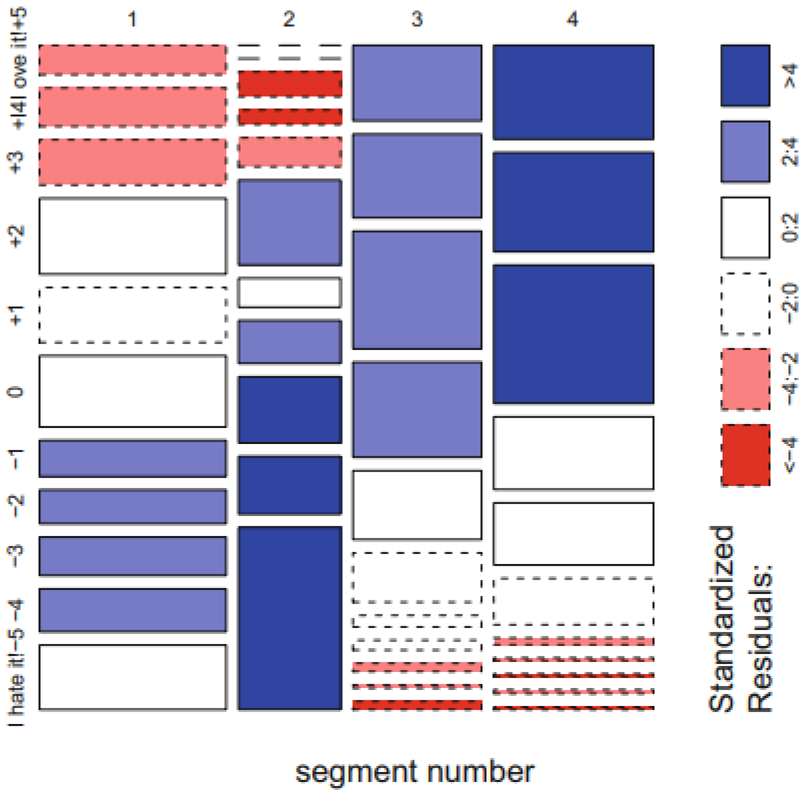
The most important details are that the fitted mixture model contains two linear regression models, one for each component, and that the significance of the parameters of each model is assessed with R> MD.ref2 - refit(MD.reg2) R> summary(MD.ref2) $Comp.1 Estimate St. Error z value Pr(>|z|) (Intercept). McDonald's is liked by segment 1 (component 1) if it is YUMMY, NOT FATTENING, FAST, CHEAP, TASTY, and NOT DISGUSTING. Segment 2 (component 2) likes it if it is CONVENIENT, NOT GREASY, HEALTHY, and NOT DISGUSTING. Argument significance controls the shading of bars to reflect the significance of parameters.

As we can see, members of segment 1 like McDonald's if they perceive it as tasty, fast, cheap and tasty, but not fattening. The horizontal lines at the end of the bars give a 95% confidence interval for each regression coefficient. For segment 2, it is important to convince members that McDonald's serves healthy food items. The core of the segmentation analysis is to create a segment profile plot to understand the four-segment k-means solution. Hierarchical clustering is used to identify the most similar attributes, which are then used to create the segment profile plot. The order of the segmentation variables is then used to create the segment profile plot.

Step 7: Describing Segments

As per diagram,the cross-tabulation of segment membership and the lovehate variable, as well as the mosaic plot of segment number and loving or hating McDonald's. The mosaic plot reveals a strong and significant association between those two variables, with members of segment 1 rarely express love for McDonald's, while members of segment 4 are significantly more likely to love McDonald's and less likely to hate it. Additionally, the mosaic plot shows gender distribution across segments, with segment 1 and segment 3 having a similar gender distribution as the overall sample. Segment 2 contains more men, while segment 4 is less likely to be men. A parallel box-and whisker plot was used to assess the association of age with segment membership. Results showed that members of segment 3 were younger than members of all other segments.

Step 7: Describing Segments



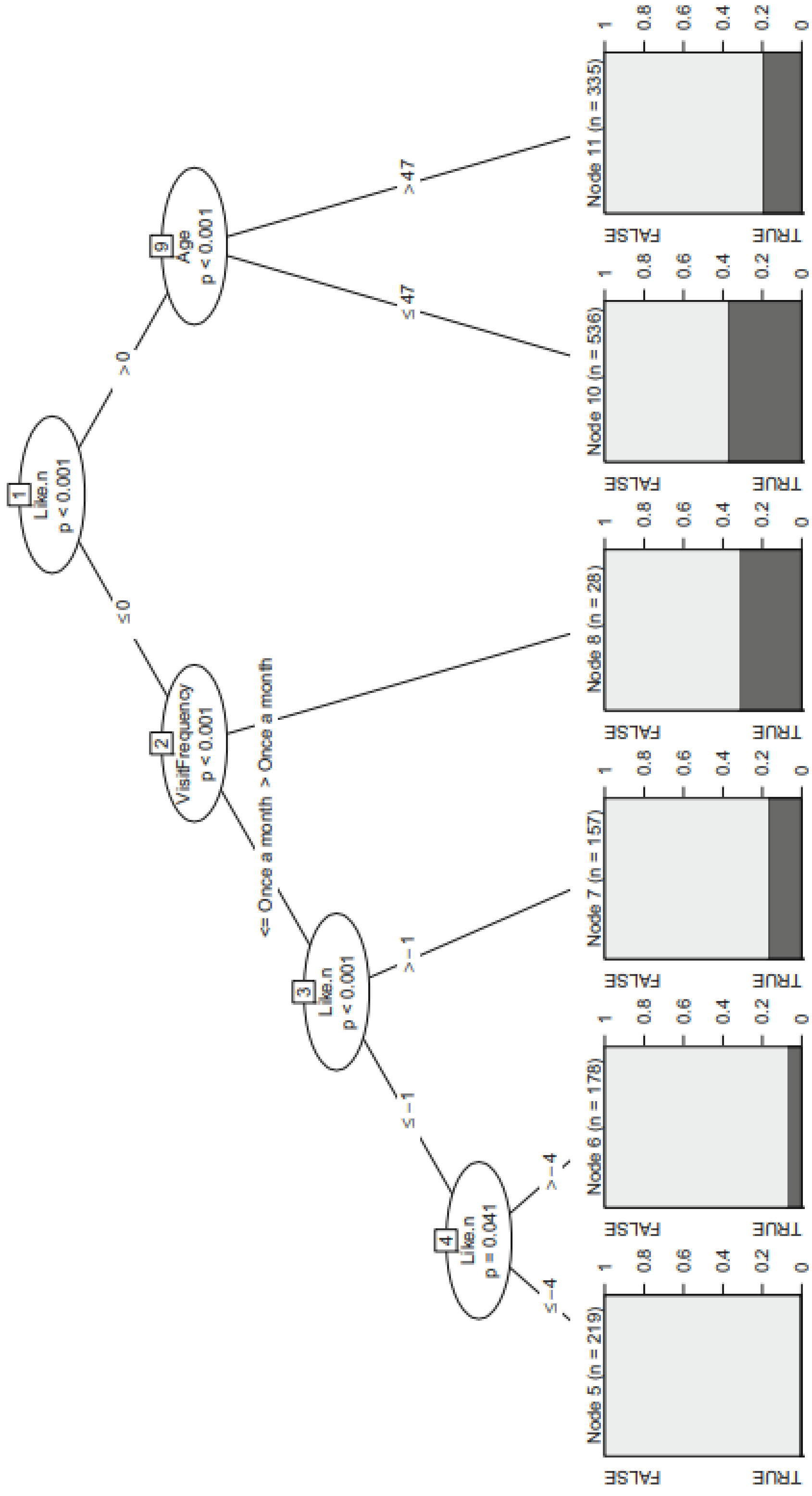
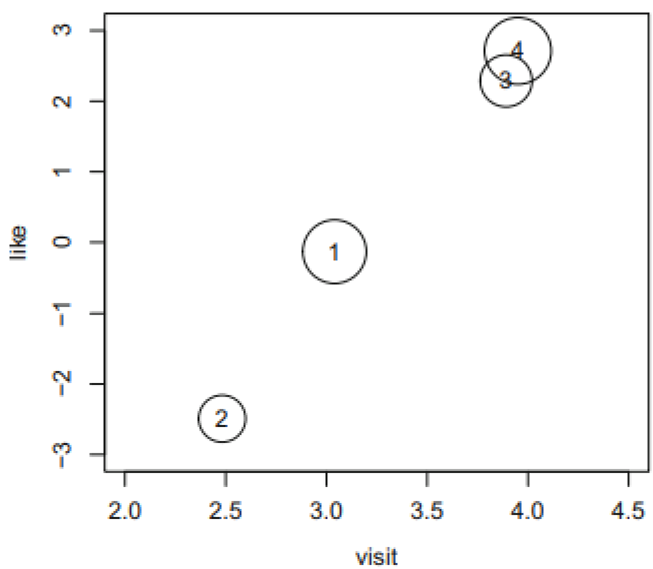


Fig. A.14 Conditional inference tree using segment 3 membership as dependent variable for the fast food data set

As we can see from the diagram, a conditional inference tree with segment 3 membership as a dependent variable and all available descriptor variables as independent variables is used to create a classification tree. This tree indicates that respondents who like McDonald’s and are young (node 10), or do not like McDonald’s, but visit it more often than once a month (node 8), have the highest probability to belong to segment 3. Additionally, additional descriptor variables such as product preferences, frequency of eating at a fast food restaurant, frequency of dining out in general, hobbies and frequently used information sources can be used to develop a detailed description of each market segment. The segment evaluation plot in Fig. A.15 is extremely simplified because only a small number of descriptor variables are available for the fast food data set. A Case Study of Fast Food Like.n p 0.001 1 0 > 0 VisitFrequency p 0.001 2 = Once a month > Once a month Like.n p = 0.041 4 4 > 4 Node 5 (n = 219) TRUE FALSE 1 0.8 0.6 0.4 0.2 0 Node 6 (n = 178) TRUE FALSE 1 0.8 0.6 0.4 0.2 0 Node 7 (n = 157) TRUE FALSE 1 0.8 0.6 0.4 0.2 0 Node 8 (n = 28) TRUE FALSE 1 0.8 0.6 0.4 0.2 0 Age p 0.001 9 47 > 47 Node 10 (n = 536) TRUE FALSE 1 0.8 0.6 0.4 0.2 0 Node 11 (n = 335) TRUE FALSE 1 0.8 0.6 0.4 0.2 0

Step 8: Selecting (the) Target Segment(s)

The segment evaluation plot is a useful decision support tool for McDonald's management to discuss which of the four market segments should be targeted. Figure A.15 shows that market segments 3 and 4 are located in the attractive quadrant, while market segment 2 is located in the least attractive position. Marketing action could attempt to address the negative perceptions of this segment and reinforce positive perceptions. The segment evaluation plot serves as a useful decision support tool for McDonald's management to discuss which of the four market segments should be targeted and become the focus of attention.



Step 9: Customizing the Marketing Mix

McDonald's management must identify communication channels and distribution channels to communicate the availability of the SUPER BUDGET line, and consider having a MCSUPERBUDGET lane to avoid cannibalizing the main product line. All potential sources of change must be monitored to detect changes that require McDonald's management to adjust their strategic or tactical marketing.

Step 10: Evaluation and Monitoring

The success of the market segmentation strategy has to be evaluated, and the market must be carefully monitored on a continuous basis. All potential sources of change have to be monitored in order to detect changes which require McDonald’s management to adjust their strategic or tactical marketing in view of new market circumstances.