Chapter 12
Step 10: Evaluation and Monitoring

12.1 Ongoing Tasks in Market Segmentation

Market segmentation analysis does not end with the selection of the target segment, and the development of a customised marketing mix. As Lilien and Rangaswamy (2003, p. 103) state segmentation must be viewed as an ongoing strategic decision process. Haley (1985, p. 261) elaborates as follows: The world changes . . . virtually the only practical option for an intelligent marketer is to monitor his or her market continuously. After the segmentation strategy is implemented, two additional tasks need to be performed on an ongoing basis:

1. The effectiveness of the segmentation strategy needs to be evaluated. Much effort goes into conducting the market segmentation analysis, and customising the marketing mix to best satisfy the target segment's needs. These efforts should result in an increase in profit, or an increase in achievement of the organisational mission. If they did not, the market segmentation strategy failed.
2. The market is not static. Consumers change, the environment, and actions of competitors change. As a consequence, a process of ongoing monitoring of the market segmentation strategy must be devised. This monitoring process can range from a regular review by the segmentation team, to a highly automatised data mining system alerting the organisation to any relevant changes to the size or nature of the target segment.

12.2 Evaluating the Success of the Segmentation Strategy

The aim of evaluating the effectiveness of the market segmentation strategy is to determine whether developing a customised marketing mix for one or more segments did achieve the expected benefits for the organisation. In the short term,

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the primary desired outcome for most organisations will be increased profit. For non for profit organisations it may be some other performance criterion, such as the amount of donations raised or number of volunteers recruited. These measures can be monitored continuously to allow ongoing assessment of the segmentation strategy. In addition, taking a longer term perspective, the effectiveness of targeted positioning could be measured. For example, a tracking study would provide insight about how the organisation is perceived in the market place. If the segmentation strategy is successful, the organisation should increasingly be perceived as being particularly good at satisfying certain needs. If this is the case, the organisation should derive a competitive advantage from this specialised positioning because the target segment will perceive it as one of their preferred suppliers.

12.3 Stability of Segment Membership and Segment Hopping

A number of studies have investigated change of market segment membership of respondents over time (Boztug et al. 2015). In the context of banking, Calantone and Sawyer (1978) find that – over a two-year period of time – fewer than one third of bank customers remained in the same benefit segment. Similarly, Yuspeh and Fein (1982) conclude that only 40% of the respondents in their study fell into the same market segment two years later. Farley et al. (1987) estimate that half of all households change in a two-year period when segmented on the basis of their consumption patterns. Müller and Hamm (2014) confirm the low stability of segment membership over time in a three-year study. Paas et al. (2015) analyse the long-term developments of financial product portfolio segments in several European countries over more than three decades. They use only cross-sectional data sets for the different time points, but are able to identify changes in segment structure at country level over time, implying instability of segment membership.

Changes in segment membership are problematic if (1) segment sizes change (especially if the target segment shrinks), and if (2) the nature of segments changes in terms of either segmentation or descriptor variables. Changes in segment size may require a fundamental rethinking of the segmentation strategy. Changes in segment characteristics could be addressed through a modification of the marketing mix.

The changes discussed so far represent a relative slow evolution of the segment landscape. In some product categories, segment members change segments regularly, they *segment hop*. Segment hopping does not occur spuriously. It can be caused by a number of factors. For example, the same product may be used in different situations, and different product features may matter in those different situations; consumers may seek variety; or they may react to different promotional offers. Haley (1985) already discussed the interaction of consumption occasions and benefits sought, recommending to use both aspects to ensure maximum insight.

For example, the following scenario is perfectly plausible: a family spends their vacation camping. Their key travel motives are to experience nature, to get away from the hustle and bustle of city living, and to engage in outdoor activities. The family stays for two weeks, but their expenditures per person per day are well below those of an average tourist. Imagine that one of the parents, say the mother, is asked – after the family camping trip – to complete a survey about their last vacation. Data from this survey is used in a market segmentation analysis and the mother is assigned to the segment of NATURE LOVING FAMILIES ON A TIGHT BUDGET. A month later, the mother and the father celebrate their anniversary. They check into a luxury hotel in a big city for one night only, indulge in a massage and spa treatment, and enjoy a very fancy and very expensive dinner. Now the mother is again asked to complete the same survey. Suddenly, she is classified as a BIG SPENDING, SHORT STAY CITY TOURIST.

These tourists segment hop. This phenomenon has previously been observed and segment hopping consumers have been referred to as *centaurs* (Wind et al. 2002) or *hybrid consumers* (Wind et al. 2002; Ehrnrooth and Grönroos 2013).

Consumer hybridity of this kind – or segment hopping – has been discussed in Bieger and Laesser (2002), and empirically demonstrated in the tourism context by Boztug et al. (2015). The latter study estimates that 57% of the Swiss population display a high level of segment hopping in terms of travel motives, and that 39% segment hop across vacation expenditure segments.

Ha et al. (2002) model segment hopping using Markov chains. They use self-organizing maps (SOMs) to extract segments from a customer relationship management database; and Markov chains to model changes in segment membership over time. Lingras et al. (2005) investigate segment hopping using a modified self-organizing maps (SOMs) algorithm. They study segment hopping among supermarket customers over a period of 24 weeks; consumers are assigned to segments for every four week period and their switching behaviour is modelled.

Another possible interpretation of the empirical observation of segment hopping is that there may be a distinct market segment of *segment hoppers*. This notion has first been investigated by Hu and Rau (1995) who find segment hoppers to share a number of socio-economic and demographic characteristics. Boztug et al. (2015) also ask if segment hoppers are a segment in their own right, concluding that segment hoppers (in their tourism-related data set from Swiss residents) are older, describe themselves more frequently as calm, modest, organised and colourless, and more frequently obtain travel-related information from advertisements.

Accepting that segment hopping occurs has implications for market segmentation analysis, and the translation of findings from market segmentation analysis into marketing action. Most critically, we cannot assume that consumers are well behaved and stay in the segments. Optimally, we could estimate how many segment members are hoppers. Those may need to be excluded or targeted in a very specific way. Returning to our example: once the annual vacation pattern of the camping family is understood, we may be able to target information about luxury hotels at this family as they return from the camping trip.

12.4 Segment Evolution

Segments evolve. Like any characteristic of markets, market segments change over time. The environments in which the organisation operates, and actions taken by competitors change. Haley (1985), the father of benefit segmentation, says that not following-up a segmentation study means sacrificing a substantial part of the value it is able to generate. Haley (1985) proceeds to recommend a tracking system to ensure that any changes are identified as early as possible and acted upon. Haley refers to the tracking system as an *early warning system* activating action only if an irregularity is detected. Or, as Cahill (2006) puts it (p. 38): Keep testing, keep researching, keep measuring. People change, trends change, values change, everything changes.

A number of reasons drive genuine change of market segments, including: evolution of consumers in terms of their product savviness or their family life cycle; the availability of new products in the category; and the emergence of disruptive innovations changing a market in its entirety.

To be able to assess potential segment evolution correctly, we need to know the baseline stability of market segments. The discussions in Sects. 2.3, 7.5.3, and 7.5.4 demonstrate that – due to the general lack of natural segments in empirical consumer data – most segmentation solutions and segments are unstable, even if segment extraction is repeated a few seconds later with data from the same population and the same extraction algorithm. It is critical, therefore, to conduct stability analysis at both the global level and the segment level to determine the baseline stability. Only if this information is available, can instability over time be correctly interpreted.

Assuming that genuine segment evolution is taking place, a number of approaches can simultaneously extract segments, *and* model segment evolution over time. The MONIC framework developed by Spiliopoulou et al. (2006) allows the following segment evolution over time: segments can remain unchanged, segments can be merged, existing segments can be split up, segments can disappear, and completely new segments can emerge. This method uses a series of segmentation solutions over time, and compares those next to each other in time. For the procedure to work automatically, repeated measurements for at least a subset of the segment members have to be available for neighbouring points in time; the data needs to be truly longitudinal.

A similar approach is used by Oliveira and Gama (2010). In their framework, the following taxonomy is used for changes in segments over time:

- Birth: a new segment emerges.
- Death: an existing segment disappears.
- Split: one segment is split up.
- Merge: segments are merged.
- Survival: a segment remains almost unchanged.

The procedure can only be automated if the same consumers are repeatedly segmented over time; data must be truly longitudinal. The application by Oliveira and Gama (2010) uses three successive years, and, in their study, the clustered objects are not consumers, but economic activity sectors. If different objects are available in different years (as is the case in typical repeat cross-sectional survey studies), the framework can still be used, but careful matching of segments based on their profiles is required.

To sum up: ignoring dynamics in market segments is very risky. It can lead to customising product, price, promotion and place to a segment that existed a few years ago, but has since changed its expectations or behaviours. It is critical, therefore, to determine stability benchmarks initially, and then set up a process to continuously monitor relevant market dynamics.

Being the first organisation to adapt to change is a source of competitive advantage. And, in times of big data where fresh information about consumers becomes available by the second, the source of competitive advantage will increasingly shift from the ability to adapt to the capability to identify relevant changes quickly. Relevant changes include changes in segment needs, changes in segment size, changes in segment composition, changes in the alternatives available to the segment to satisfy their needs as well as general market changes, like recessions.

McDonald and Dunbar (1995, p. 10) put it very nicely in their definition of market segmentation: Segmentation is a creative and iterative process, the purpose of which is to satisfy consumer needs more closely and, in so doing, create competitive advantage for the company. It is defined by the customers' needs, not the company's, and should be re-visited periodically.

Example: Winter Vacation Activities

To illustrate monitoring of market segments over time, we use the data set on winter activities of tourists to Austria in 1997/98 (see Appendix C.2). We used this data set in Sect. 7.2.4.2 to illustrate bagged clustering. Here, we use a reduced set of 11 activities as segmentation variables. These 11 activities include all the key winter sports (such as alpine skiing), and a few additional activities which do not reflect the main purpose of people's vacation. Importantly, we have the same information about winter activities available for the 1991/92 winter season. These two data sets are repeat cross-sectional – rather than truly longitudinal – because different tourists participated in the two survey waves.

Package MSA contains both data sets (`wi91act`, `wi97act`). We can load the data, and calculate the overall means for all activities for 1991/92 and 1997/98 using the following R commands:

```
R> data("winterActiv2", package = "MSA")
R> p91 <- colMeans(wi91act)
R> round(100 * p91)

      alpine skiing cross-country skiing          ski touring
                 71                   18                    9
```

```
   ice-skating        sleigh riding                 hiking
             6                   16                     30
      relaxing             shopping          sight-seeing
            51                   25                     11
       museums           pool/sauna
             6                   30
```

```
R> p97 <- colMeans(wi97act)
R> round(100 * p97)
```

```
alpine skiing cross-country skiing           ski touring
           68                    9                     3
  ice-skating        sleigh riding                hiking
            5                   14                    29
     relaxing             shopping          sight-seeing
           74                   55                    30
      museums           pool/sauna
           14                   47
```

The resulting output lists the winter activities, along with the percentage of tourists in the entire sample who engage in those activities. We visualise differences in these percentages across the two survey waves using a dot chart (Fig. 12.1). The vertical grid line crosses the x-axis at zero; dots along the vertical line indicate that there is no difference in the percentage of tourists engaging in that particular winter activity between survey waves 1991/92 and 1997/98. The following R code generates the dot chart of sorted differences, and adds a vertical dashed line at zero (`abline()` with line type `lty = 2`):

```
R> dotchart(100 * sort(p97 - p91),
+    xlab = paste("difference",
+    "in percentages undertaking activity in '91 and '97"))
R> abline(v = 0, lty = 2)
```

Figure 12.1 indicates that the aggregate increase in pursuing a specific activity is largest for shopping (shown at the top of the plot): the percentage of tourists going shopping during their winter vacation increased by 30% points from 1991/92 to 1997/98. The largest decrease in aggregate activity level occurs for cross-country skiing. For a number of other activities – ice-skating, hiking, sleigh riding, and alpine skiing – the percentages are almost identical in both waves.

So far we explored the data at aggregate level. To account for heterogeneity, we extract market segments using the data from the 1991/92 winter season. In a first step we conduct stability analysis across a range of segmentation solutions. Stability analysis indicates that natural market segments do not exist; the stability results do not offer a firm recommendation about the best number of segments to extract. Based on the manual inspection of a number of alternative segmentation solutions with different numbers of market segments, we select the six-segment solution for further inspection.

We extract the six-segment solution for the 1991/92 winter season data using the standard k-means partitioning clustering algorithm:

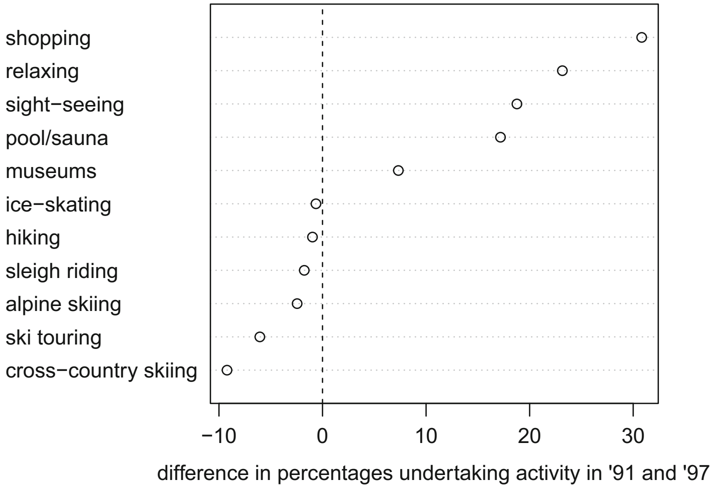

Fig. 12.1 Difference in the percentage of tourists engaging in 11 winter vacation activities during their vacation in Austria in 1991/92 and 1997/98

```
R> library("flexclust")
R> set.seed(1234)
R> wi91act.k6 <- stepcclust(wi91act, k = 6, nrep = 20)
```

where `k` specifies the number of segments to extract, and `nrep` specifies the number of random restarts.

We then use the following R code to generate a segment profile plot for the 1991/92 data. We highlight marker variables (`shade = TRUE`), and specify for each panel label to start with `"Segment "`:

```
R> barchart(wi91act.k6, shade = TRUE,
+   strip.prefix = "Segment ")
```

Figure 12.2 contains the resulting segment profile plot. We see that market segment 1 is distinctly different from the other segments because members of this segment like to go hiking, sight-seeing, and visiting museums during their winter vacation in Austria. Members of market segment 2 engage in alpine skiing (although not much more frequently than the average tourist in the sample), and go to the pool/sauna. Members of market segment 3 like skiing and relaxing; members of segment 4 are all about alpine skiing; members of segment 5 engage in a wide variety of vacation activities, as do members of segment 6.

To monitor whether – six years later – this same market segmentation solution is still a good basis for target marketing by the Austrian National Tourism Organisation, we explore changes in the segmentation solution in the 1997/98 data set. We first use the segmentation solution for 1991/92 to predict segment memberships in 1997/98. Then we assess differences in segment sizes by determining the percentages of tourists assigned to each of the segments for the two waves:

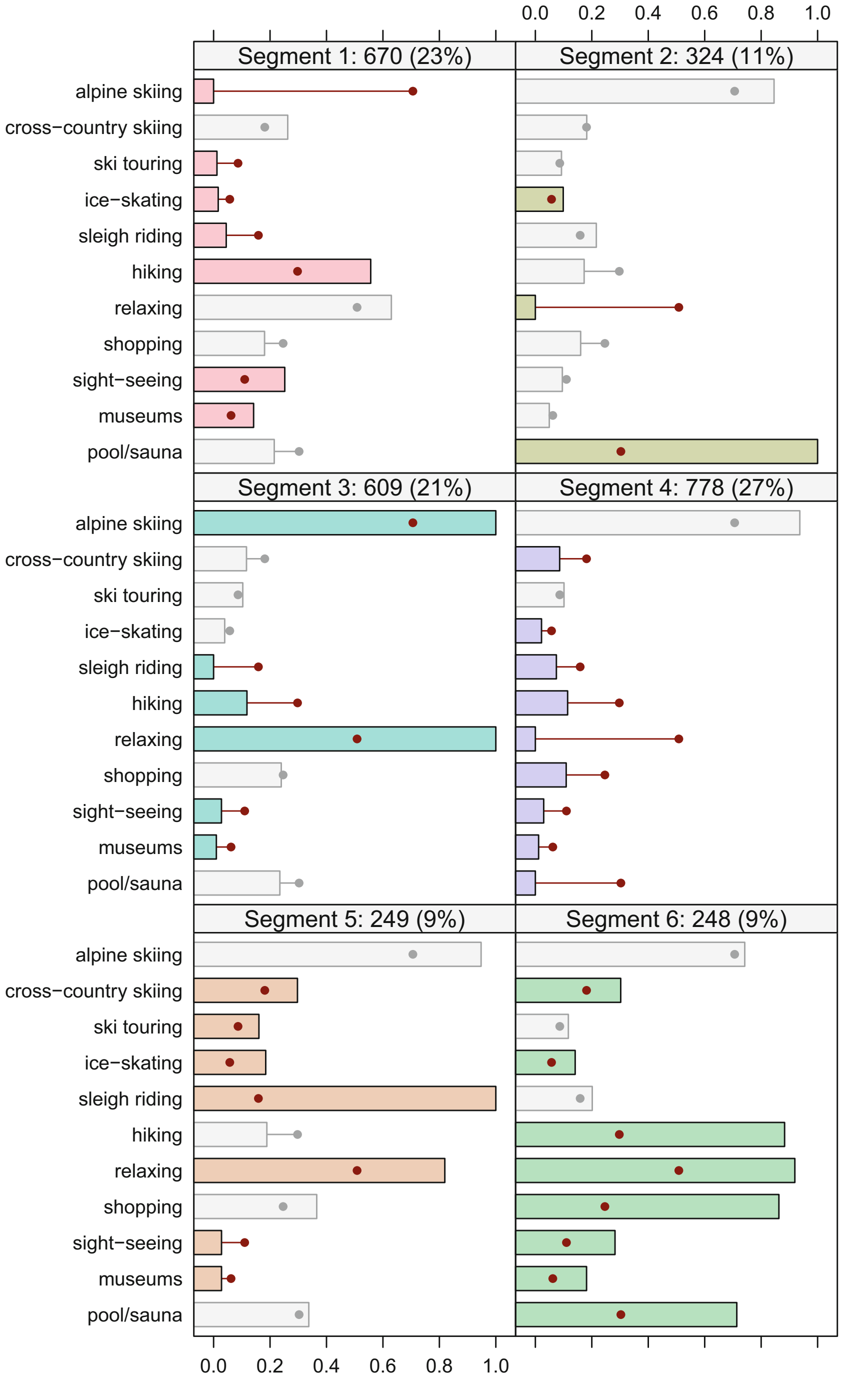

Fig. 12.2 Segment profile plot for the six-segment solution of winter vacation activities in 1991/92

```
R> size91 <- table(clusters(wi91act.k6))
R> size97 <- table(clusters(wi91act.k6,
+   newdata = wi97act))
R> round(prop.table(rbind(size91, size97), 1) * 100)
```

```
        1  2  3  4 5  6
size91 23 11 21 27 9  9
size97 22  7 29 12 9 21
```

The comparison of segment sizes indicates that segments 1 and 5 are relatively stable in size, whereas segments 4 and 6 change substantially. We use a χ^2-test to test if these differences could have occurred by chance:

```
R> chisq.test(rbind(size91, size97))

        Pearson's Chi-squared test

data:  rbind(size91, size97)
X-squared = 375.35, df = 5, p-value < 2.2e-16
```

The χ^2-test indicates that segment sizes did indeed change significantly. We can visualise the comparison in a mosaic plot (Fig. 12.3):

```
R> mosaicplot(rbind("1991" = size91, "1997" = size97),
+   ylab = "Segment", shade = TRUE, main = "")
```

The mosaic plot indicates that some segments (1 and 5) did not change in size, that segment 4 shrunk, and that segment 6 nearly doubled. Depending on the target segment chosen initially, these results can be good or bad news for the Austrian National Tourism Organisation. If we also had descriptor variables available for both periods of time, we could also study differences in those characteristics.

In a second step we assess the evolution of market segments. We extract segments from the 1997/98 data. Optimally, we would use truly longitudinal data (containing

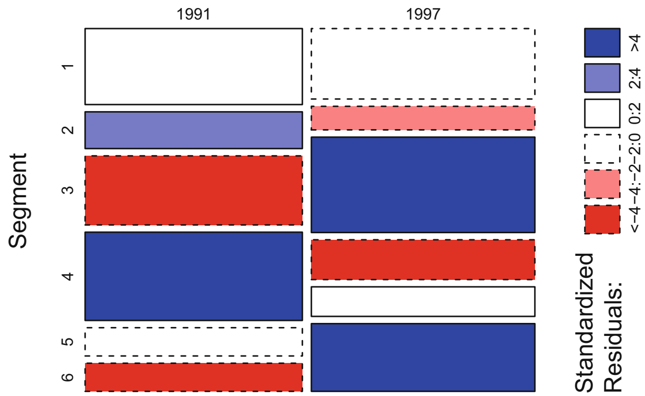

Fig. 12.3 Mosaic plot comparing segment sizes in 1991/92 and 1997/98 based on the segmentation solution for winter activities in 1991/92

responses from the same tourists at both points in time). Longitudinal data would allow keeping the segment assignment of tourists fixed, and assessing whether segment profiles changed over time. Given that only repeat cross-section data are available, we extract new segments using centroids (cluster centres, segment representatives) from the 1991/92 segmentation to start off the segment extraction for the 1997/98 data. We obtain the new segmentation solution using the previous centroids as initial values (argument `k`) for *k*-means clustering of the 1997/98 data using:

```
R> wi97act.k6 <- cclust(wi97act,
+    k = parameters(wi91act.k6))
```

The following R command generates the segment profile plot for the market segmentation solution of the 1997/98 data:

```
R> barchart(wi97act.k6, shade = TRUE,
+    strip.prefix = "Segment ")
```

We see in Fig. 12.4 that the resulting segmentation solution is very similar to that based on the 1991/92 data. We can conclude that the nature of tourist segments has not changed; the same types of tourist segments still come to Austria six years later.

Segment evolution is visible in the variable shopping, pursued to a large extent by tourists in segment 6 and nearly half of all tourists. The aggregate analysis already pointed to this increase in shopping activity: a quarter of winter tourists to Austria went shopping in 1991/92; more than half did so in 1997/98. This change might be explained by the liberalisation of opening hours for shops in Austria in 1992.

Another obvious difference is the change in segment sizes. Segment 4 (interested primarily in alpine skiing) contained 27% of tourists in 1991, but only 13% in 1997. Segments 3 and 6 increased substantially in size, suggesting that more people combine alpine skiing with relaxation, and more people engage in a broader portfolio of winter activities.

These changes in segment sizes have implications for the Austrian National Tourism Organisation. While in 1991/92 a third of winter tourists to Austria would have been quite satisfied to ski, eat and sleep, the Austrian National Tourism Organisation would be well advised six years later to offer tourists a wider range of activities.

Fig. 12.4 Segment profile plot for the six-segment solution of winter vacation activities in 1997/98

12.5 Step 10 Checklist

Task	Who is responsible?	Completed?
Convene a segmentation team meeting.		☐
Determine which indicators of short-term and long-term success will be used to evaluate the market segmentation strategy.		☐
Operationalise how segmentation success indicators will be measured and how frequently.		☐
Determine who will be responsible for collecting data on these indicators.		☐
Determine how often the segmentation team will re-convene to review the indicators.		☐
Determine which indicators will be used to capture market dynamics.		☐
Remind yourself of the baseline *global stability* to ensure that the source of instability is attributed to the correct cause.		☐
Remind yourself of the baseline *segment level stability* to ensure that the source of instability is attributed to the correct cause.		☐
Operationalise how market dynamics indicators will be measured and how frequently.		☐
Determine who will be responsible for collecting data on market dynamics.		☐
Determine how often the segmentation team will re-convene to review the market dynamics indicators or whether the collecting unit will pro-actively alert the segmentation team if a meeting is required.		☐
Develop an adaptation checklist specifically for your organisation of things that need to happen quickly across the affected organisational units if a critical change is detected.		☐
Run the indicators, measures of indicators, reviewing intervals and the draft adaptation checklist past the advisory committee for approval or (if necessary) modification.		☐

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