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Abstract

Market segmentation has become one of the fundamental building blocks of strategic marketing during the last decades. Although the methodology of deriving market segments from survey data became more and more sophisticated, no operationalized list of selection criteria for alternative segment options has been introduced so far to the authors' knowledge.

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Keywords: market segmentation, target segment choice

Segment Evaluation Criteria Reviewed

Ever since the late 60ies, market segmentation received great attention within the field of strategic marketing research. A wide number of different issues connected to the segmentation concept has been studied, e.g. the nature of variables underlying the grouping of individuals, the grouping techniques used to create segments, the number of market segments to split the respondents into etc. At the same time, the number of applications increased steadily, as demonstrated in a meta-analysis conducted by Baumann (Baumann, 2000).

Despite the strong interest of both practitioners and academics in market segmentation, there was very little research on evaluation of potential target segment and the systematic choice of the optimal target segment and the ex post evaluation of how successful certain segment decisions turned out to be in the marketplace. Clearly, to answer the latter question the cooperation of companies is indispensable that might to be forced to admit failure, which dramatically complicates investigation. The first two issues could be investigated in more detail by turning to a more quantitative approach. The basis for formalising the issue of segment evaluation and target segment choice is provided by the market segmentation milestone publication authors, who all recommend evaluation criteria in a qualitative manner:

Frank, Massy and Wind (Frank et.al, 1972) require operational market segments to be (1) sufficiently different from one another on the one hand and to be (2) reachable in an efficient manner through the available promotional vehicles. Kotler (Kotler, 1988) suggests that segments should possess a number of characteristics: mutual exclusiveness, exhaustiveness, measurability, accessibility, substantiality and difference in response to marketing strategy. Lilien and Kotler (Lilien and Kotler, 1983) postulate only three factors: homogeneity, parsimony and accessibility where homogeneity is understood as reaction similarity among members of the same segment, parsimony calls for a small set of large segments and accessibility refers to the possibility to characterise the target groups by observable variables. A highly management-oriented approach is chosen by McDonald and Dunbar (McDonald and Dunbar, 1995). They list a wide variety of possible criteria that determine a segment's attractiveness, some of them include: growth rate of revenue spent by each segment, accessible segment size (revenue less revenue impossible to access, regardless of investment made), and profit potential. Wedel and Kamakura (Wedel and Kamakura, 1998) summarise the segment requirements by stating six relevant criteria: identifiability, substantiality, accessibility, stability, responsiveness and actionability. Identifiability refers to the possibility to reveal segment membership of a consumer in the marketplace. Substantiality represents the segment size with the main emphasis lying on the profitability of marketing action. Accessibility refers to the ability to reach the selected target group with communicative marketing instruments. Stability over time is a prerequisite at least over one period in order for marketing action to be effective. Responsiveness stands for unique reaction of the segment members to any kind of marketing action and finally actionability calls for the compatibility of the target segment chosen with the core competencies of a company.
McDonald (McDonald, 1999) lists the following requirements: adequate size in view of the return, high degree of similarity among segment members as well as high degree of distinction to remaining segments in these variables, segment description criteria should be relevant for the purchase situation, and reachability of segment members. Although numerous - strongly convergent - criteria can be found in literature, there are very few endeavours to propose a systematic evaluation tool of segment attractiveness. Wedel and Kamakura recommend the use of standard portfolio analysis, McDonald and Dunbar also suggest the application of either the Boston Consulting Portfolio tool or the McKinsey multi-factor extension of this concept. In addition the authors present a simple step-by-step process for evaluation and choosing the optimally suited market segment that consists of the following stages: (1) Defining segment attractiveness criteria. (2) Weighting segment attractiveness criteria. (3) Setting segment scores for the criteria. (4) Calculating segment values. (5) Establishing the company's ability to compete in each segment.

To sum up the results, the literature review on market segment attractiveness criteria and segment choice support tools reveal two major shortages:

1. **Lack of operationalized evaluation criteria**: Although a wide variety of criteria has been proposed by different authors, there are no attempts to operationalize these criteria in a way to make them computable and thus transform them into quantitative measures that could easily be calculated for practical purposes. As a consequence of this lack of formal operationalization, there seems to be some inconsistency in naming the criteria.

2. **Lack of structured decision procedures**: Even if a list of computable criteria existed, it is not clear, how to combine these criteria for the purpose of making a final segment choice decision. Portfolio models still dominate this field, unreflectedly assuming that either two criteria are sufficient (Boston Consulting group matrix) or combined attractiveness measures used as axis values (McKinsey Business Attractiveness portfolio) are naturally constructed in a completely compensatory manner. Even the best evaluation criteria might suffer from such simplified decision heuristics.

**Operationalizing segment evaluation**

This chapter provides a number of operationalized segment attractiveness evaluation criteria, that are based on some of the theoretical recommendations described in the previous section. For ease of comparison, the criteria suggested in the milestone publications are listed in Table 1. For all criteria that have been operationalized, the names are given in the third column. As basis for the calculation of most of these figures disaggregated survey data is assumed to be available. Also, the starting point is a segment solution which could e.g. be the result of a cluster analytic procedure.

<table>
<thead>
<tr>
<th>criterion</th>
<th>theoretical recommendation</th>
<th>proposed index</th>
</tr>
</thead>
<tbody>
<tr>
<td>size</td>
<td>substantiality, parsimony</td>
<td>absolute, relative size</td>
</tr>
<tr>
<td>profitable size</td>
<td>return, money size, growth rate</td>
<td>profit margin</td>
</tr>
<tr>
<td>stability</td>
<td>stability over time</td>
<td></td>
</tr>
<tr>
<td>accessability</td>
<td>reachability</td>
<td></td>
</tr>
<tr>
<td>similar features</td>
<td>similarity</td>
<td>feature similarity</td>
</tr>
<tr>
<td>different features</td>
<td>distinction</td>
<td>feature difference</td>
</tr>
<tr>
<td>degree of concentration</td>
<td>size as compared to competitors</td>
<td>changes in shares</td>
</tr>
</tbody>
</table>

| changes in shares | |

Obviously, one of the simplest criteria is **absolute size**. "The more potential consumers, the better" would be the typical reasoning underlying this measure.

\[ n_{i,s} = \sum_i \sum_j e_{ij,s} \]  

(1)

where \( e_{ij,s} \) is an indicator of segment affiliation \((0,1)\) of the \(i^{th}\) customer, of the \(j^{th}\) product.
The relative size indicate the market segment share of a particular brand.

\[
\tilde{n}_{st} = \frac{\sum_i c_{it} \cdot e_{it,t} \cdot e_{it,t}}{\sum_j c_{jt} \cdot e_{jt,t} \cdot e_{jt,t}}
\]  

(2)

where \(c_{it}\) are the choices (purchases) of customer \(i\) of product \(t\) (my product) at time \(t\). Neither absolute, nor relative size take into account, that different segments might be willing to pay different prices for the same product. This is where the concept of profitable sizes comes in (profit margin). Of course, the underlying assumption is that the cost structure of competing firms is the same as it is the case for the own firm. For every cluster:

\[
P_{st} = \sum_i \sum_j (w_{ij} - v_{ij} - f_{ij} / \sum c_{ij}) \cdot c_{ij} \cdot e_{yt,t} \cdot e_{yt,t}, \quad \tilde{P}_{st} = P_{st} / \max P_{st}
\]  

(3)

where \(w_{ij}\), \(v_{ij}\), and \(f_{ij}\) are the price demanded for a product, the variable and fixed cost, respectively. Feature similarity is typically the assumption underlying all traditional partitioning algorithms that cluster multivariate data without taking into account any kind of dependent variables. Such techniques include k-means, learning vector quantisation, all hierarchial clustering procedures but also self organising neural partitioning approaches. From the managerial point of view this criterion means:

Find individuals with similar characteristics and treat them the same way. Let

\[
d_{st} = \sum_k \left( 1 - \left( \sum_i \sum_j \sum_l \sum_{t'} (x_{ijk,t'} - x_{ij't'})^2 \cdot e_{yt,t'} \cdot e_{yt,t'} \right) / (IJ - 1) \right)
\]  

(4)

where \(x_{ijk,t}\) is the belief (our foundation of the clusters) of the \(ith\) customer of the \(jth\) product of the \(kth\) attribute at time \(t\) \((j \neq i')\). High values of inner variance indicate high similarity of the respondents within one market segment. Feature difference is nothing else but the reverse side of feature similarity. Methodologically all traditional algorithms comply with this requirement as members of different clusters obviously differ in the characteristics given in the data set. The operationalization for management also is reversed:

Treat individuals with different characteristics in a different manner. Let:

\[
x_{ijk,t} = \sum_i \sum_j \phi \left( \sum_l \sum_{t'} \left( x_{ijk,t'} - x_{ij't'} \right)^2 \cdot e_{yt,t'} \cdot e_{yt,t'} \right)
\]  

\[
u_{st} = \sum_l \left( \sum_i \sum_j \left( x_{ijk,t} - x_{ij't} \right)^2 \cdot e_{yt,t} \cdot e_{yt,t} \right) / (IJ - 1)
\]  

(5)

High values of outer variance indicate high differentiation between market segments. Competition might be a factor that has to be included in the market segment choice process. One possibility is to simply use the segment unit market share. The higher the market share, the less competition is encountered (= size as compared to competitors):

\[
b_{st} = \sum_i c_{it} \cdot e_{it,t} / \sum_i \sum_j e_{jt,t}
\]  

(6)

In a second step, the strongest competitor in each segment can easily be traced down by searching for the maximum market share of the competitors.

\[
b_{st} = \frac{\tilde{b}_{st} \cdot e_{it,t}}{\tilde{b}_{st} \cdot e_{it,t}}
\]  

(7)

where \(b_{st}\) is the strongest competitor in the segment. Another possible indicator for the intensity of competition and the strength of the own company in the marketplace is the "changes in shares" index which investigates the development over time.

\[
a_{st} = \frac{\sum_i (c_{it,t} - c_{it,t-1}) \cdot e_{it,t} \cdot e_{it,t}}{\sum_i (c_{it,t} - c_{it,t-1}) \cdot e_{it,t} \cdot e_{it,t}}
\]  

(8)
Systematic Segment Choice Rules

For many decades the choice behaviour of consumers has received great attention and a wide variety of different choice rules have been suggested in a realistic multi-attribute decision making setting. MacCrimmon (MacCrimmon, 1996) and Engel et al. (Engel, Blackwell and Miniard, 1993) have developed a systematic overview of consumer decision rules. MacCrimmon divides the decision rules into four categories (weighting, sequential elimination, mathematical programming and spatial proximity methods) with three sub-categories in each. In the following paragraphs one noncompensatory and two compensatory decision rules, namely lexicography (elimination), simple additive weighting and multidimensional scaling (proximity) are explained.

Under the lexicographic decision rule an importance ranking of attributes on an ordinal scale is established. The segment with the highest value in the "most important" feature is chosen. If more than one segment passes this requirement, the second attribute in the ranking is taken into account. This process is repeated until one single segment remains. Let

\[ A = (n_{x}, \hat{n}_{x}, \hat{p}_{x}, d_{x}, u_{x}, \hat{b}_{x}, \hat{a}_{x}) \]

be a \( s \times 7 \) matrix to be evaluated. The next step is to set up the ranking vector for the seven attributes and start the elimination. Ties until the seventh attribute are solved. Simple additive weighting directly assesses a weight to each of the seven attributes. The weights are then multiplied with the attribute values and summed up to give an integrated evaluation value. The weights are chosen according to the corporate philosophy. The segment rendering the maximum index value is chosen as target segment.

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\[ \left( \frac{\alpha_{1}}{n_{r}} + \frac{\alpha_{2}}{\hat{p}_{r}} + \frac{\alpha_{3}}{d_{r}} + \frac{\alpha_{4}}{u_{r}} + \frac{\alpha_{5}}{\hat{b}_{r}} + \frac{\alpha_{6}}{\hat{a}_{r}} \right) \]

where \( \alpha_{1} \) to \( \alpha_{7} \) are the weights \((0,1)\) and the first and the last four indexes are normalised to \((0,1)\). As compared to the lexicographic rule, the simple additive weighting process is purely compensatory. This could be a potential danger in a group decision making context, unless the weight definition process is handled with great care. A very nice feature of the additive weighting process is that artificial learning algorithms (simulated annealing, neural networks, genetic algorithms) can easily be included to optimise weights over time. Multi-dimensional scaling belongs to the family of ideal point models. The fundamental assumption is that an ideal target segment can be constructed. This segment can be characterised by attribute values and thus represent a point in multidimensional space. The best segment choice based on this fundamental assumption is the group of respondents that is closest to this ideal point. By calculating the Euclidean distances from each cluster to the ideal point this optimally suited segment can easily be identified. Thus, the firm has to decide on an ideal point in terms of the segment attributes \( i \). In the second step the Euclidean distance \( ||i-A|| \) for each segment is computed and the cluster with the minimum distance is chosen. Of course, any corporate philosophy can be mirrored in either a ranking vector a weight vector or an ideal segment point. By making use of typical consumer choice behaviour models, the decision of which target segment to choose thus becomes much more reflected and structured at three levels: First, the decision which attributes should be used to evaluate the segment has to be thoroughly analysed. The choice and operationalization of these attributes forms the basis of the target segment decision. Second, a decision technique has to be chosen. Of course, a firm could also decide to start off with a lexicographic phase choosing only segments surpassing a target level of a particular criterion and then apply a weighted additive model to the remaining segments. Again, deciding on the technique induces an insightful managerial discussion process and thus leads to a more conscious and systematic segment choice. This same argument is true for the third aspect: the definition of the ranking vector, the weighting vector or the ideal segment point. All in all, the segment choice process certainly requires some
thinking and some discussion but it increases understanding of the problem, customises marketing action to corporate objectives and philosophies and thus reduces unharmonized subjective and thumb-rule based segment choices. Of course, both the list of segment evaluation criteria as well as the number of choice rules can be further extended for practical use in corporate decision making.

**Conclusions**

Widely accepted consumer choice rules were applied in a managerial decision making setting: the choice of the optimal market segment to serve. As it is the case in a consumer buying decision, management is confronted with a number of segments and each one of the segments has favourable and less favourable characteristics. By (1) applying operationalized and computable attractiveness criteria and (2) systematic combination rules of this criteria typical in multi-attribute decision making, the entire process of segment selection, is made more transparent and systematic. In addition, the wide variety of decision rules allows management to gain insights into the structure of the problem. Future research work can go in two different directions: On the one hand it would be highly interesting to empirically investigate, how segment choice decisions are actually made in corporate environments and compare these findings with theoretical choice rule knowledge. This might allow determination of decision choice inefficiencies which could be reduced by implementing structured decision processes. On the other hand it makes sense to investigate which decision rules are superior to other in general. For this purpose, the decision rules would have to be implemented in an artificial environment under controlled conditions. Such simulations could increase understanding of different decision rules using different segment evaluation criteria under various environmental conditions.

From the practitioner's point of view, the framework provided can certainly be further extended both in terms of the criteria to be included for the purpose of segment evaluation as well as the decision rules used for systematic decision processing.

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**References**


