BRAND POSITIONING IN ESTABLISHED MARKETS: NEW APPROACHES IN "EVERYDAY MARKETING"

by Elmar Haimerl and Ralph Ohnemus *

ABSTRACT

Data analysis in market segmentation and brand positioning studies is orientated primarily towards the ideal of the launch of innovative, differentiated brands which form a new sub-category in the market. However, everyday marketing is not about establishing new sub-categories, but about gaining a foothold in existing markets, achieving market leadership there or defending such a position, for example. Assessments of market segmentation studies based on false ideals deliver misleading signals, however, and are thus in part responsible for the high rate of flops. This article shows which analysis steps are required in order to obtain information with which success can be achieved in existing markets.

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1. *Current marketing practice and the idea of differentiated brands*

A fundamental task of marketing is to boost sales. New offerings or new brands are an important means towards achieving this aim. But in the case of existing brands as well the task is to find "drivers" or to remove barriers. If one listens to marketing consultants or follows popular marketing literature, only one suitable approach for brand success exists: differentiation.

This is in fact an old marketing concept (*Chamberlin* 1933, *Robinson* 1933 or *Smith* 1956), but it still forms the basis of modern marketing. The concept of market segmentation and differentiation has largely been accepted for a long time both by marketing practitioners and in academic circles. By making it possible to divide markets into clearly distinct groups of customers which react in different ways to the variables in the marketing mix, it was thought that a way had been found to address consumers more precisely and thus exert greater influence upon them.

Differentiation can increase the profitability of a brand if it reduces the degree of competition with other brands, thus providing scope for higher prices (cf. e.g. *Sharp & Dawes* 2001, p. 6). Therefore, in the view of many marketing consultants, differentiation is the only means of survival (cf. *Trout* 2001), divergence the escape from the dilemma of price ruin or failure in the market (cf. for example *Schüller* not dated, *Heinz* 2007).

Empirical studies also support this view: Young and Rubicam's "Brand Asset Valuator", for example, shows that differentiated brands leave their "peers" lagging far behind in terms of profit and market growth (cf. *Bernstein* 2007, p. 20).

However, in many cases the companies lack the financial means, the time and the innovations. According to B. *Feldhusen* (2005) of A. C. Nielsen, only just under 3% of new products which appear on the market are genuine innovations, i.e. products which did not exist before. The market research institute Fessel-GfK (2006) estimates that 53% of all new products are characterized by a low degree of innovation, while the respective figures for medium and high innovation are 28% and 19%. Depending on definition, product area and demarcation, the failure rate of new products is estimated to be as high as 90 percent (within two years of launch). Here, as a rule it is assumed that genuine novelties, i.e. differentiating brands, come off better, while „me-toos" fail significantly more frequently. According to an analysis by *Stadler* (2006), which assumes a relatively low failure rate, so-called me-toos, in other words brand launches with a low level of differentiation, have a success rate of 18.4%, products with a middling level of benefits a rate of 32.4% and products which are truly innovative a rate of 53.5%. The question of whether a brand is to be regarded as a me-too may also be dependent on how successful it is or was. However, this is not the place to quibble over numbers. Regardless of which figures are correct, imitation products are commonplace. What is also indisputable is that new products seen as me-toos are often but not always flops. However, the same also applies to truly innovative or differentiated products.

Furthermore, it is striking that the differences in the perception of existing brands are of such small magnitude. Above all, Professor *Ehrenberg et al.* (e.g. *Kennedy, Ehrenberg & Long* 2000; *Kennedy & Ehrenberg* 2001) have shown that **competing brands** within a product category are purchased by **very similar consumers**. If brands substantially differentiated themselves from each other, however, they would by definition also have to appeal to significantly different buyers. Market research, Ehrenberg suggests, has attempted to place the focus on revealing differences which in fact do not exist or are insignificant, and if a company then seeks to concentrate on a particular segment, it merely limits the spread of consumers who will buy its product (cf. also *Hammond et al.* 1996). This would make market segmentation almost counter-productive. Or, as Sharp puts it: "Being competitive means selling to the market, not a special segment" (*Sharp/Tolo/Giannopoulos* 2001).

Therefore the demand for differentiation appears to a considerable extent to run counter to marketing reality. Does this mean companies should give up the idea of differentiation?

2. *Market segmentation and cluster analyses*

2.1 *Cluster analysis as a method for defining target groups*

The prevailing approach in market research for identifying the market potential of possible new brands is market segmentation; especially „benefit segmentation" (cf. *Haimerl/Ohnemus*, 2005).

Here, the needs of consumers are ascertained and groups are worked out on this basis with the help of cluster analysis processes. Marketing believes that on the basis of particular group characteristics it can identify the group or groups whose needs are not yet being adequately met by the current market, and who would be pleased by a better, more differentiated product offering. In this way marketing supposedly obtains the desired orientation for the development of a superior offering – at least in one subgroup (cf. *Haimerl/Ohnemus*, 2005).

But why, in spite of this, are there so many me-toos according to almost all of those engaged in marketing? And, more importantly, why are there so many flops?

The most important group of statistical analysis methods for market segmentation on the basis of several variables is referred to mainly – including here – as "cluster analysis". However, there are a number of other terms, such as automatic classification (cf. *Bock*, 1974), mathematical taxonomy or taxonometry (cf. *Jardine* and *Sibson*, 1971), "unsupervised learning" (e.g. *Jain/Dubes*, 1988), vector quantization (cf. *Oehler/Gray*, 1997) and so on. It is almost impossible to get an overview of the literature on this subject. Important books in this area include *Jain* and *Dubes* (1988); *Anderberg* (1973); *Hartigan* (1975); *Späth* (1980); *Duran/Odell* (1974), etc. In addition to these there are also a number of important and influential overview articles such as *Jain et al.* (1999) or *Berkin* (2002).

Market segmentation methods based on cluster analyses (e.g. benefits segmentations) became very popular in the 1970s. For these, **hierarchical** cluster analysis techniques were mostly used. Historically, these originate in taxonomy as used in biology, where organisms are classified according to relationships.

In the field of marketing, the greatest interest was focused on finding few, large target groups for brands. Hierarchical methods, however, prove to be unable to offer sufficient overview and to require too much computation in the case of large data sets. Furthermore, the commonly used agglomerative methods produced sub-optimal solutions at a high aggregation level. They are therefore largely replaced by **non-hierarchical** methods for market research purposes.

The underlying idea of the non-hierarchical, partitioning techniques is to classify a number of objects in a given number of sub-groups/clusters randomly or according to a pre-specified solution and subsequently shift the objects iteratively until an optimization criterion – e.g. the minimal variance – is reached (mostly k-means or k-medoid algorithm). However, despite considerable effort on the part of researchers there still remain questions which can only be answered imprecisely: How many clusters are there? What measure of similarity or difference should be used? Which criterion precisely is to be optimized? How should anomalies be treated, etc.?

No doubt the most common approach of that time and certainly also today is the so-called "tandem approach". Here, a factor or principal component analysis is first applied to the variables that are to be clustered. This serves to reduce the number of variables and to identify "independent" dimensions. The resulting "factor scores" are then clustered, typically with the k-means algorithm (assuming the independence of the variables).

Arabie and *Hubert* (1994), in particular, have strongly criticized this practice, with the argument that the data is distorted to a significant degree by this process: The original, differing mean scores of the data, they argue, become the same (with a mean of zero), the differing mean variations equalized and thus their significance made to conform. And, finally, they can see no justification for many non-correlating dimensions (factors) being created, if the aim of cluster analysis is to identify and depict correlations. Overall, they claim, due to this practice the structure contained in the data is completely changed and distorted (cf. *Arabie* and *Hubert* 1994). This quite substantial criticism has, however, only had a modest effect on the practice of market research.

Alongside this classical procedure, in the course of time a plethora of other cluster analysis algorithms have been developed (cf. especially *Han/Kamber*, 2000). In the meantime there are hundreds of different classification strategies, with clearly different outcomes.

It was recognized early on that cluster analyses can also be based on probability distributions (for an overview see e.g. *Bock*, 1996). These procedures are often called model-based methods, "finite mixture models" or mixed distribution models; also the familiar "latent class analysis" would today be included in this category of procedures (cf. e.g. *Jain et al.*, 1999).

Density-based cluster procedures have been developed in order to be able to represent clusters with irregular forms.

Some algorithms, such as grid-based algorithms, work indirectly with the data. Thus they are especially suitable for searching large and high-dimensional data sets.

A number of cluster analysis methods arose from the basic thinking behind biological neuronal networks. Familiar methods are Kohonen's "learning vector quantization" (LVQ) and "self-organizing map" (SOM) (cf. *Kohonen* 1984, 2001).

When using cluster analysis one is thus faced with the problem – as this brief overview shows – of having to choose an appropriate and „correct" classification method. However, this seems to be no easy task.

2.2 *Which cluster analysis method is the right one?*

When there are so many differing methods, there has to be a criterion for deciding which is to be used for a particular question. *Kaufmann & Pape* (1984, pp. 471f.) recommend judging the results in terms of "useful" and "non-useful". *Jain et al.* (1999, p. 290) take a similar view. Thus it is above all practical logic which decides which cluster analysis method is considered appropriate. Just as it is possible to correctly group whales, elephants and sharks in various ways, such as water-dwelling and land-based creatures or equally precisely into mammals and fish – the same applies to cluster analyses. It is not a matter of right or wrong, but of the question as to what form a sub-division should take in order to achieve a specific goal or to answer a particular question.

For this reason, in the next step we will consider the analysis methods normally used in market research practice in more detail, before we investigate the consequences arising from the fact of the often small differentiation of segmentation characteristics.

3. *Optimization criteria and results of partitioning cluster analysis procedures*

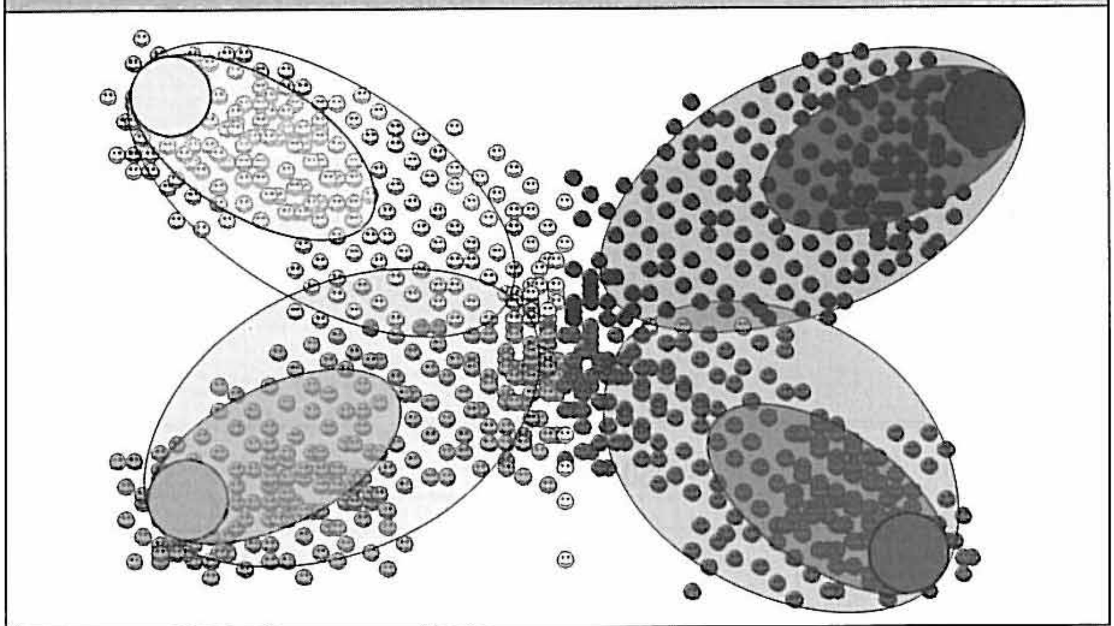
The results of cluster analyses – as we mentioned above – are neither right nor wrong; each cluster analysis procedure subdivides a group according to the different pre-specified criteria, which are more or less suitable for a question. The criterion for the predominantly used partitioning procedure is the minimization of the mean variation: the clusters in themselves should be as homogeneous as possible and the differences between the clusters as large as possible.

The reproduction in *Figure 1* of the market segmentation of an international market leader can be seen as typical (the dark areas symbolize the cluster centres). This presentation alone should raise suspicions among heads of marketing departments or other users of cluster analyses for marketing purposes.

If we assume that in our society the bulk of consumers are still „in the centre ground", then we need to ask whether it is wise not to have this centre ground covered. Thus there may occur a gap in the market and there is tremendous potential for a brand occupying it. Brands such as Cremissimo, Orange, Always and Rexona have in our view

Figure 1

Typical representation of clusters



capitalized on these chances. The reason for this neglect of the centre ground is the optimality criterion of partitioning cluster procedures. They seek to maximize the differences between the clusters/target groups.

If a market only contains relatively weakly differentiating dimensions, as Ehrenberg and others (e.g. *Kennedy/Ehrenberg/Long* 2000; *Kennedy/Ehrenberg* 2001, *Sharp/Tolo Giannopoulos* 2001) have shown for many markets, then two further consequences result which, however, do not become apparent when – as usual – the already-mentioned tandem method is used:

- The level differences between the dimensions and the absolute size of the differences between the target groups are concealed.
- Furthermore, cluster analyses tend to generate as many differences as possible.

1. The concealment of the level differences and the differences between the clusters

Partitioning cluster analyses presuppose the independence of the variables. Since, as a rule, this is not the case, a factor analysis – as described above – is applied to the variables, and all further calculations (therefore the cluster analyses in particular) are made using the so-called "factor scores", i.e. standardized values which can simply be described as combinations of the individual variables measured.

This can be demonstrated in the following results, which may be seen as typical. Let us assume that the factor scores of the requirements regarding the product category based on (hypothetical) clusters are as in *Table 1*:

The summary in *Table 1* gives (as intended) the impression that cluster 1 had high requirements regarding factor 1 (pleasure in this case), cluster 2 even higher ones con-

Table 1

Factor Scores of 3 clusters (hypothetical example)

	Cluster 1	Cluster 2	Cluster 3
Factor 1 (e.g. pleasure)	0.70	- 0.45	- 0.30
Factor 2 (e.g. health)	- 0.30	1.03	- 0.40
Factor 3 (e.g. rapid effect)	0.05	- 0.25	0.42

cerning factor 2 (health), and cluster 3 the highest for its factor (rapid effect). In that case, however, there would be three target groups with significantly different requirements regarding the product category.

However, if one looks not only at the factor scores but also at the mean values of the respective individual statements one notices that the differences between the judgement dimensions are significantly greater than those between the clusters. A 5-point scale forms the basis of what follows below, in which 5 represents the most positive expression. For each factor in this hypothetical example there are 3 statements with "high loadings" – see *Table 2*.

Table 2

Factor scores and mean values of the factor-forming statements			
	Cluster 1	**Cluster 2**	**Cluster 3**
Factor 1 (pleasure)	**0.70**	- 0.45	- 0.30
Tastes particularly good	4.7	4.3	4.4
Is pure pleasure	4.2	4.0	4.2
You can spoil yourself with it	4.3	4.1	4.1
Factor 2 (health)	- 0.30	**1.03**	- 0.40
Is a particularly healthy product	2.7	3.2	2.6
Contains valuable vitamins	2.1	3.1	2.0
Offers high performance in advanced years	2.3	3.2	2.2
Factor 3 (rapid effect)	0.05	- 0.25	**0.42**
Statement 1	3.0	2.9	3.3
Statement 2	3.1	2.8	3.4
Statement 3	3.5	3.0	3.7

The comparison shows that factor 1 was the only one regarding which truly high requirements were placed upon the product in the category in question by the consumers interviewed – in fact, by all respondents. By comparison, the differences between the clusters are rather marginal. This means that all respondents desire first and foremost what factor 1 measures (pleasure); the "wishes" regarding dimensions/factors 2 and 3, on the other hand, are expressed only weakly. However, the differences erroneously indicated in the factor scores come far closer to human thinking and therefore to the thinking of those responsible for marketing and market research. People tend to think in terms of strongly differentiated groups, in stereotypes: men are from Mars, women from Venus, Swiss are one way, Germans the other. Major differences are more vivid and more easily learned; they demarcate and make decisions easier.

A recent article by *Rao* (2008) still interprets this as a superior procedure: principal component analysis and the use of the (standardized) factor scores, as well as subsequent centering of the data leads to results which, in comparison to other methods (such as latent-class analysis), are especially "descriptively rich and actionable" (*Rao,* 2008, p. 13). One does indeed get that impression! But it is highly questionable whether the stringing together of different methods, each of which drastically alters the data, leads one closer to the „truth".

If instead one does not use the tandem approach but calculates the clusters, for example, on the basis of indices (the sum of the high-loading statements divided by their number), then one really does see „what's going on". However, for many marketing managers this remains an unsatisfactory result, precisely because "weakly separated clusters" appear as unsatisfactory: one does not really know what to do with that. A possible consequence of this is: to return to the tandem approach after all.

2. The generation of the largest possible number of differences

The second, and for that matter the most problematic, characteristic of partitioning cluster analyses is that they spread out the differences between the clusters found – due to the optimization criterion – over as many dimensions as possible (factors, statements, etc.). Even if the differences between the clusters "in reality" are not very pronounced, cluster analysis seeks to maximize the differences. This works best in mathematical terms if all variables make a contribution (however small). If the requirements differ only moderately, clusters will be formed which differ a little in the greatest possible number of dimensions: here a little more, there a little less. However, precisely this last point is incompatible with the conditions for the success of a new product on an existing market.

4. *Partitioning cluster analyses and conditions for success within existing markets*

In order to be successful within existing markets, new products have to meet **three requirements**:

- They have to show clearly that they belong to the product category in question, i.e. clearly cream cheese, chocolate or an SUV
- They have to be "better" in some (or several) dimensions – at least for a sub-group of consumers
- And they have to be of interest to a sufficiently large target group

As explained above, cluster analyses – especially in the form of partitioning methods shown – maximize the differences between the groups or clusters, and we have seen that this is easiest when each variable provides „a little" mean variation. If major differences really are shown, this points to the possibility of establishing a new category – a "brand monopoly". A new sub-category has to build up a new "schema". In Germany, Actimel, for example, were able to show much more clearly than LC1 or Vifit that their product was not merely a yoghurt but a kind of over-the-counter medication. However, if – as in most cases – the differences are less clear or the aim is to enter a new market, cluster analysis provides **false** information on what has to be done: it does not show clearly what central dimension (or dimensions) can serve as additional benefits or a better "reason why"; instead, it encourages marginal movements away from the existing market offerings, for example from the market leader or "first mover".

The findings suggest that a new, allegedly differentiating product can be launched which in many respects is a **little** different from the products already on the market. This only serves to confuse the consumers: "*Is this something new? Does it still belong to the familiar category that I know as yoghurt, butter or cream cheese? Or is it actually something different?*" But what does data analysis have to provide in order to identify (at least) the one "USP" that offer the opportunity to be successful in an existing market, in other words to establish a successor product with sufficiently large market potential?

The new product would have to show that it clearly belongs to one market, such as, for example, the hatchback category of cars, or butter, or chocolate. Yet it also has to be better – at least for pårt of the target group – in at least one dimension than the existing products on the market. Here the aim should be not only to serve a distinct group of consumers but also the **largest possible group of consumers** better than others do. Data analysis should identify as large a group of consumers as possible which may even be identical with the mass of other consumers in virtually all the requirement dimensions, but who, in at least one respect, want something different (a „benefit") or believe something different is more credible ("reason why, reason to believe"). However, the partitioning method does not provide this. Which methods then are suitable for this purpose?

5. *Bundle optimization as an alternative method for analysis of market positioning studies and for identification of target groups*

In our presentation of cluster analysis algorithms we showed that the predominant partitioning methods in particular (such as k-means or k-medoid) are unsuitable for defining the position a new brand has to take up in order to be successful in an existing market. They aim for maximum differentiation instead of maximum buyer reach and they differentiate on the basis of the greatest possible number of dimensions and not of the few that one has to focus on.

Conversely, however, these cluster analysis methods are well suited to helping really innovative brands to succeed. This is because truly innovative products have to create a new sub-category. Here, it is necessary to differentiate from the existing market clearly and in many dimensions. Only in this way can a new "schema" be created. But these are the (pleasant) exceptions, not everyday marketing.

Besides the partitioning method, a wealth of alternative cluster analysis algorithms are available for use. For example, if one assumes a multi-variate normal distribution of the sample (for all clusters) with finite mixture models, then, of course, the accusation of disregarding the centre does not apply: this method identifies the „centre". If, on the other hand, there are clearly demarcated dense regions of consumers, then density-based methods may be of use.

In our experience, however, the most suitable procedure is not one of the cluster analysis methods, but "bundle optimization", or, more precisely, the analysis of overlapping bundles. For dichotomous variables it delivers precisely the goal we have defined: target groups which may largely overlap, but which differ from each other in a few variables.

This approach is derived from an idea of Paul Green and Abba Krieger of The Wharton School, University of Pennsylvania (cf. for example *Green/Krieger* 1992, 1995 and *Krieger/Green* 2000).

The bundle optimization method is traditionally used mainly to determine the optimum make-up and size of ranges or the optimum combination of features of complex products. However, it can also be used with data which is otherwise used in cluster analysis. Then, instead of clusters, groups of consumers are sought who jointly show the greatest possible number of identical (dichotomous) variable expressions, i.e. who expect roughly the same benefits. If several such groups of consumers are determined, these groups may have very many identical variable expressions, as the optimization criterion is the size of the group, and not the differentiation or the „fit" to a pre-specified distribution. The data can be weighted - for instance, according to readiness to spend, in which case the optimization criterion is the expected sales. All further evaluations are identical in design to those of clusters.

What do the new analyses show?

(1) Consumers primarily buy a product category, such as butter or insurance. The new analysis clearly shows what the consumers' main requirements from the category are, and (with the help of causal analyses) how credibly it can be suggested that "our" brand meets this need better than other brands.

(3) Brands must add (at least one!) specific, differentiating benefit. Our analyses show that brands have to focus very heavily on one or only a few additional benefits. This is because with each additional benefit the group of consumers who can be reached is reduced at the same time: only a small number of consumers want a car that doubles up as a boat. More benefits can quickly turn into lower buyer potential.

(3) On a third level, needs can be met with varieties. The new analysis shows which varieties are necessary and which are actually harmful to the brand.

Therefore there are two forms of analysis for market segmentation:

- cluster analysis, which examines the question of whether there are clearly differentiated opinions or needs within a market and how these are distributed. If these clear differences exist, the chance is there to build up a new sub-category, a new "brand monopoly" (cf. *Stein* 1997).
- If this is not the case (or if the company in question cannot afford to build up a new brand monopoly), a second analysis method is available in the form of bundle optimization, with which one can sound out what needs to be done in order to perform in an existing market, for instance in order to establish a new brand which distinguishes itself positively in at least one dimension from other brands. The group of consumers which can be won in this way may, of course, even form the „centre ground", especially if this centre has hitherto not been addressed precisely enough.

This seems to have been the case in Germany with ice-cream (later occupied by Cremissimo) and deodorant (occupied by Rexona) and in the UK, for example, in the telecommunications market (Orange).

However, the new product will only be successful if this differentiating dimension is of great importance to the target group. This brings us to the question:

6. *Can the importance of the differentiating feature be significantly increased?*

We have seen that a successful brand – including a successor brand, a me-too – has to display at least one differentiating benefit besides the core benefit of the category. This also corresponds with the aesthetic principle of the "preference for prototype theory": since people tend to prefer low-risk, familiar products and at the same time have a craving for the new, a new product must involve a clearly visible novelty while at the same time retaining the typical features of the category (cf. e.g. *Whitfield* 2000). Prototypicality is therefore an important prerequisite for the esteem of a brand.

Realistically, one has to assume that the **subjective importance** of a differentiating quality is not as a rule paramount for the consumer. The same also applies to existing brands: the consumer is so used to the existing brand that it no longer acts as a real "driver". Does the possibility exist of making a relatively banal feature more important to the consumer? The magic words for this today are "**emotionalization of the brand.**"

Emotions – as we learn from both psychology and the neuro-sciences – are not separate from and independent of facts and cognitions. One cannot merely emotionalize brands by showing emotions in connection with the product. Emotions are (mainly automatic) evaluations, that is, **evaluations of the consequences** of some stimuli (cf. *Haimerl* 2007, for an overview). This means that a fact or a (differentiating) product feature has no significance for (purchasing) decisions if it is not (emotionally) valued. And, conversely, an emotion which, for example, is shown in the communication, but which is not associated with the brand or particular features, is without importance.

If emotions are evaluations of stimuli concerning the consequences for the individual, how can an emotionalization of brands (or particular features of the brand) be achieved? To do so, **two conditions** are required:

The consumers have to get involved with the communication – in other words, „**resonance**" has to be created (cf. *Haimerl/Lebok/Ohnemus* 2007). Resonance is generated if the consumer has the appropriate "schemas" for processing the information received and if these schemas also trigger the desired emotional response.

The communication has to trigger "**anticipated emotional episodes**". What does this mean? Consumers buy a product - a brand - not because the advertising is nice and triggers emotions. This only results in the advertising being well received (or not). Consumers buy a brand because they associate (predominantly) positive emotions with the **use of the product** or the **consequences** of the use of the product.

This decision-making process is habitualised. In the case of fast-moving consumer goods it suffices for a buying decision if these emotions briefly flash through the consumer's mind at the point of sale (for details, see Haimerl 2007). The details of how one reached this evaluation need not be refreshed in cases of successive decisions; in other words, they are only partially conscious.

The emotionalization of brands therefore means firstly generating resonance and then making it possible for the consumer genuinely to relate to the consequences of using the brand, directly or indirectly. Instruments such as the Resonator, for example, have already been developed as market research tools which can be used in the optimization of resonance (cf. *Haimerl/Lebok/ Ohnemus* 2007). As a suitable tool for the search for possible approaches to emotionalizing the content of communication, "Psychodrama", for example, has proven to be successful (cf. e.g. *Haimerl/Roleff* 2000).

7. *Conclusion*

The creation of "brand monopolies", i.e. new sub-categories of products or services will certainly remain the ideal goal of good, proper marketing. But there are also opportunities to successfully launch brands, even with a lower budget, if the degree of innovation remains modest and one wishes to enter existing markets and get one's "share". And „everyday marketing" is also concerned with either defending or developing existing market positions.

If one's aim is to successfully enter existing markets or to maintain or develop one's own position in such markets, it is wrong to wish to reach the clusters/target groups that are the most differentiated. That is not the marketing goal to strive for! Rather, one has to try to fulfil the core benefit of the category as well as possible and to be "prototypical" of the category. And, furthermore, it is necessary to be on the lookout for those small advantages which are of interest to a large target group and which help one to build up a true, relevant and superior benefit (USP) within a category. This concentration on the brand specifics helps to make the brand message clear and unmistakable, thus making decisions easier and provoking brand switching in favour of one's own brand. However, this often requires the courage to take apparent banalities in the product or brand really seriously.

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