The goal of customer segmentation, the cornerstone of strategy development, is to identify homogeneous groups of customers that will respond in a consistent way to changes in the marketing mix. Interpretation of traditional quantitative segmentation approaches requires an inferential leap as to the underlying decision processes of each segment. Means-end research methodologies address this problem by providing a framework to understand customer decision making that can be directly translated into the specification of positioning strategy that is more personally relevant to a given target consumer group. The quantitative marketing research orientation to means-end research is contrasted to a more qualitative, consumer-decision research perspective. A new methodological procedure that addresses the shortcomings in previous analysis methods to produce decision segments is presented.

INTRODUCTION

The strategic planning process involves determining the best course of action to achieve the strongest and most sustainable position in the marketplace. Three interrelated subprocesses provide the foundation for this effort: market segmentation, product/service positioning, and product innovation (identifying new opportunities).

At the cornerstone of strategy development is market segmentation. The basic objective of this function is to identify homogeneous groups or customer segments in the marketplace that will respond in a consistent, predictable way to variations in the marketing mix. The orientation used to identify these segments requires developing an understanding of the marketplace from a customer perspective. Why this is so important is aptly summarized by Drucker (1976, p. 146):

A business is not defined by the company’s name, statuses, or articles of incorporation. It is defined by the wants the customer satisfies when he [or she] buys a product or service... The question “What is our business?” can, therefore be answered only by looking at the business from the outside, from the view of the customer and the market. What a customer sees, thinks, believes and wants, at any given time, must be accepted by management as an objective fact... All he [or she] is interested in are his [or her] own values, his [or her] own wants, his [or her] own reality.

Drucker may be summarily paraphrased by saying the only reality that defines the marketplace is in the minds of customers, not in the board room. This understanding of the customer directly translates into the second component of strategic planning; the optimizing of a product/service positioning. By first identifying segments and their size, and then gaining an understanding of the individual commonality of perception and motivation within each segment, the marketer can select the most advantageous target segments and optimally position the product/service specifically to the defining decision criteria. This customer orientation also serves to emphasize the fact that positioning is not about delineating the
simple quantifiable attributes of the product from a manufacturer’s perspective; rather, it lies in the minds of customers that drive choice. In other words, the primary focus of segmentation should be on understanding how customers (past, current, and “potential” future) perceive the product/service in terms of their own decision making, thereby resulting in brand engagement.

The traditional approach to quantitative segmentation methods suggest that the initial research question to be answered is:

Who are my customers? What characteristics differentiate them from the competition (demographics, psychographics, purchasing behavior, needs/attitudes, personal values)?

This type of information permits the market researcher to infer what customers are like; more specifically, the inference is regarding what the primary determinants are in their buying decision processes. The inferential understanding that results from the segmentation question then provides the basis for approaching the following marketing decision:

How do (and should) we optimally differentiate our offering(s) from the competition?

The underlying marketing premise is that by gaining an understanding of customers, in particular, the needs and wants that drive their decision processes, the marketer can develop a specific positioning that will appeal more effectively to them. Additionally, this insight also should direct the third process—product/service innovation—essentially focusing on the potential “need-and-want hot buttons” that are most likely to be successful for product extension and new-product development. In sum, once this customer understanding results in insights as to the (decision-making) structure of the marketplace, it serves as the basis of the marketing planning process, in particular, target market selection and the development of tactical plans, with respect to the elements of the marketing mix.

The traditional market research techniques that are intended to define customer segments require obtaining measures of the most appropriate customer characteristics and subjecting these to various multivariate statistical methods to investigate their potential discriminatory power with respect to the competition. (For a detailed summary of both data required and analysis methods, see Myers, 1996.) The resulting output of this research is segments that are named, quantified, and summarized with descriptive narratives, along with their respective differentiating behavioral tendencies. An example of the segmentation of the automobile industry can be found in Table 1. These segments, in this case derived from attitudinal statements, are then used as a basis to determine the additional differentiating characteristics with respect to lifestyle, media habits, etc. Although this example of segmentation is very simplistic, it does illustrate the general type of summary output that serves as the basis for developing customer understanding and how it would serve, with the addition of media and other external variables, as key input into the development of marketing strategy.

However, these inferential methods of gaining consumer insight, as determined

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**Research methods fall short in terms of gaining a true understanding of customer choice, in their failure to specify both what is critical and why it is important to the customer.**

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**TABLE 1**

<table>
<thead>
<tr>
<th>Category</th>
<th>Percentage</th>
<th>Description</th>
<th>Make</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automophiles</td>
<td>24%</td>
<td>Know a lot about cars and enjoy working on them</td>
<td>Dodge, Pontiac</td>
</tr>
<tr>
<td>Sensible-centrists</td>
<td>20%</td>
<td>Prize practicality</td>
<td>Volvo, AMC</td>
</tr>
<tr>
<td>Comfort-seekers</td>
<td>17%</td>
<td>Favor options and luxury models</td>
<td>Jaguar, Mercedes, Lincoln</td>
</tr>
<tr>
<td>Necessity-drivers</td>
<td>13%</td>
<td>Prefer an alternative way of traveling</td>
<td>AMC</td>
</tr>
<tr>
<td>Autophobes</td>
<td>12%</td>
<td>Care most about safety</td>
<td>Oldsmobile, Mercury</td>
</tr>
</tbody>
</table>

by customer clusters or segments, do not provide a clearly specified model of the underlying decision-making process that permits a more detailed and consumer-motivating form of positioning to be developed. That is, these research methods fall short in terms of gaining a true understanding of customer choice, in their failure to specify both what is critical and why it is important to the customer. As illustrated with this automobile example, the marketer must generalize from prior experience specifically what is driving or motivating the importance of a differentiating perception that underlies preference and consumption. This lack of a definitive causal relationship, between the motivations underlying choice and the buying decisions of interest, creates a disconnect in which inference must provide the necessary bridge. It is this requirement—to infer what the drivers of choice are for segments—that makes traditional segmentation research less than optimal for the development of a more consumer-engaging brand positioning.

A superior methodology of defining segments, eliminating the inferential subjectivity, would be one that provides customer understanding of both the What and Why questions, eliminating this disconnect. Myers (1996, pp. 263–79), in his review of segmentation methods, discusses the potential of means-end research and the qualitative laddering methodology (Reynolds and Gutman, 1988) for providing the connection between the discriminating attributes and the personal reasons why they are important. Myers (1996, p. 263) posits:

... (the laddering methodology) was developed to gain an understanding of how consumers think about a product or service category or an activity. In the process of doing this, it attempts to identify the attributes that drive preference and choice within a category. It also reveals the linkages among these key attributes... this identifies... [the] “decision making structure” of a consumer. Once these attributes and linkages (to personal motivations/values) are understood, they can be used to form a positioning strategy ... based on the translation of an attribute into the personally relevant reasons why it is important to the consumer. [Emphasis added]

The potential of such a qualitative methodology, based upon the understanding the consumer decision-making process, to develop market segmentation is significant. Not only does it resolve the inferential problem associated with the traditional segmentation techniques, it also lends itself to providing the basis for optimizing the development of product/service positioning (Olson and Reynolds, 1983; Reynolds and Craddock, 1988). Moreover, such a decision-grounded approach to identifying segments can be seen as the most efficacious way to classify customers, essentially ensuring the likelihood of a predictable response to variations in the marketing mix—the guiding principle of all segmentation.

This article first reviews the methodological foundation of alternative means-end approaches to segmentation, contrasting a market research orientation to a more qualitative one more directly grounded in understanding the customer choice process. The article then details a new segmentation methodology, based upon qualitative research methods for understanding brand choice, and explains why it provides a superior framework to develop and optimize positioning strategy.

BACKGROUND
Means-end theory
The “means-end approach” has at its foundation the notion that decision makers choose courses of action (purchase behavior) that will achieve their desired outcomes or end-states (Gutman, 1982). Means-end research methods focus on deriving chains (MECs) that represent an association network of meaning, from attributes to functional consequences to psychosocial consequences to personal values. Values are generally defined as the important beliefs people hold about themselves and their feelings regarding others’ beliefs about them (Rokeach, 1968). According to means-end theory, values (V) provide the overall direction and give meaning to desired consequences (C). A desirable consequence (i.e., that satisfies a higher order value) determines what attributes (A) of the choice option are salient, which define the competitive behavioral options. By uncovering the important network of meanings for a category in this way, the marketer is provided with an in-depth understanding of how customers perceive the marketplace.

Howard and Warren (2000, p. xi) summarize the means-end theoretical perspective as:
A decision-grounded approach to identifying segments can be seen as the most efficacious way to classify customers, essentially ensuring the likelihood of a predictable response to variations in the marketing mix—the guiding principle of all segmentation.

... cognitive structure of meaning that connects a product’s attributes to the consequences of product use ... these chains of meaning were critical to understanding both how and why consumers make purchase decisions. Thus, the means-end approach represents a more personalized, more emotional, more personal, more idiosyncratic version of how consumers think and make decisions about which products to buy to satisfy their needs.

Clearly, the means-end perspective offers a solution to answering the What and Why questions necessary for increasing the usefulness and accuracy of market segmentation research as a basis for the development of optimal brand strategy.

Before a review of the taxonomy of means-end research methods is undertaken, it is worthwhile to note a few additional theoretical considerations with overriding research design implications. In his original theory article, Gutman (1982) posits that it is the consumption occasion that provides the basis to determine which consequence is desirable, which necessarily means that different MECs will result depending upon the situational context in which it is grounded. Recognizing this initial question framing issue is critical; research methods directed toward eliciting the most meaningful anchors of MECs are based upon such things as timing of purchase or consumption as well as preference or usage differences by occasion (Reynolds, Dethloff, and Westberg, 2001; Woodside, 2004). It is the understanding of the bases of consumer preference within the “surrounding context” (e.g., occasion or need state) that permits the marketer to develop a more comprehensive specification of the brand positioning.

Means-end methods: Market research versus decision research orientations

Means-end research methods have evolved into two different orientations to approaching the problem of obtaining MECs: market research and decision research. To provide a framework for understanding the trade-off between these methods for developing positioning strategy, a review of the underlying assumptions and rationales for each approach will be highlighted. Figure 1 presents a graphical summary of the means-end research orientations, along with exemplary articles that will be explicated for each research area. The numbers embedded in the chart denote the discussion order.

1. Cognitive research: The cognitive orientation of Means-End Theory (Gutman, 1982) led to the development of laddering (Reynolds and Gutman, 1988), a structured, qualitative research technique comprised of four components:
   a. Eliciting important category distinctions (attributes) for each respondent.
   b. Probing for higher-level meanings. This is accomplished by a version of the “Why is that important to you?” question. The initial distinction is typically used as the basis to move respondents “up the ladder” of abstraction, from attributes to values, which represents a complete MEC. The chain length output from the questioning process varies by both attribute and respondent (typically, four or five levels).
   c. Content coding. The qualitative results of the probes are subjected to content analysis, resulting in a set of summary codes (usually 25–35) across the levels of abstraction.
   d. Constructing the hierarchical value map (HVM). The frequencies of the connections, or implications (both direct and indirect), between the codes are computed. A direct implication means A directly preceded C in the MEC, and indirect means A preceded V in the...
Figure 1 Means-End Research Orientations
MEC, but not directly. A direct-implication threshold value that accounts generally for 70% percent of the total implications is selected. All direct implications above the threshold value are considered significant, which are then represented by connecting lines drawn between the codes in a hierarchically-ordered dendogram or directed graph. The standard approach to this deterministic approach of capturing the dominant connections is to investigate multiple cutoff thresholds, with the researcher subjectively determining the "most representative," or category-defining, MEC structure. This required choice of the cutoff level for this deterministic type of analysis is obviously quite problematic in the sense that the exact same set of laddering data can result in different HVM representations, depending upon the research analyst’s decision. The resulting HVM, then, represents all the significant adjacent-level connections, with no explicit understanding of the indirect relations. (This major shortcoming will be addressed later.)

Figure 2 represents such a hypothetical HVM from the light beer category, which includes suggested graphical enhancements with respect to the relative frequency of the code and the strength of the connections (Gengler, Klenosky, and Mulvey, 1995). The four levels of abstraction represented (attributes, functional consequences, psychosocial consequences, and values) are the standard in means-end research (Olson and Reynolds, 2001).

2. Positioning applications: The interpretation of the HVM, then, is that any connecting pathway from the bottom to the top represents a perceptual orientation that can be considered as an option for developing a potential positioning (Olson and Reynolds, 1983). By specifying positioning strategy across the four levels of meaning in this way, the presumption is that it will be more meaningful to the consumer, tapping into their higher level motivations. Although this is certainly an approach to develop a myriad of positioning options, the lack of a statistically-grounded way to identify and evaluate the dominant, common pathways makes this process highly researcher dependent and subject to criticism (Grunert and Grunert, 1995). Noteworthy is the finding from a proprietary meta-analysis of 70+ nonalcoholic beverage advertisements across seven countries that the communication of and the connection to the higher level components add significantly to generating persuasion. Put simply, the more the MEC is linked from bottom to the top, the more persuasive the communication.

A prototypical example of developing positioning strategy in this way, noted in Figure 1, is for overnight delivery services (Reynolds and Craddock, 1988). The extension to the assessment of the strength of communication and the level of connection between the strategic elements, creating a complete MEC decision network, using political candidates and social issue examples may be found in Reynolds, Westberg, and Olson (1997).

3. Market research: The traditional laddering methodology to uncover MECs, as a basis for the strategy development
process, suffers from two significant limitations: it is time consuming and costly to conduct one-on-one interviews, and it is necessary to employ a highly trained interviewer (Hofstede, Audenaert, Steenkamp, and Wedel, 1998). To resolve this, Hofstede, Audenaert, Steenkamp, and Wedel (1998) propose a more efficient, "paper and pencil" marketing research methodology (Association Pattern Technique or APT) to obtain MECs, which utilizes a predetermined list of attributes, consequences, and values (three levels), although it is suggested that the number of levels could be enlarged. In this example, the APT methodology presents two matrices to the respondent (attribute-consequence and consequence-value), both of which represent all possible combinations between levels. The respondent is asked to identify the key association for each row (level i) to the column (level i + 1) for both matrices. This quantitative approach to obtaining MECs, which is amenable to mail survey research, is designated as "hard" laddering, as compared to the "soft," in-depth interviewing methodology of laddering (Grunert and Grunert, 1995).

Although the economies of the "hard" marketing research orientation to obtaining MECs are obvious, several questions emerge (noted in the box adjacent to [4] in Figure 1):

a. Codes. The a priori determined codes can be justified given adequate prior research. Yet, one has to question if the meanings are consistently interpreted by the respondent in the case of values, as well as the possible effect of bias when responding to such abstract concepts. (This is especially of issue for international and cross-cultural applications.) Of course, no verbatim output from this method. These verbatim oftentimes provide a clearer understanding of what to specify for the positioning strategy and serve as key input for the creative development process. This is particularly true when dealing with the imagery associated with communicating at the higher levels of abstraction.

b. Levels. As noted, three levels of abstraction are used in APT. However, the question remains about the resulting quality of the data when the respondent is confronted with this additional fourth level of complexity. Given that the missing level is psychosocial consequences, which have been shown as the most meaningful level in terms of persuasive advertising (Reynolds and Trivedi, 1989), this would appear to be an additional limiting barrier to its use for developing and specifying positioning strategy.

c. Task. Hofstede, Audenaert, Steenkamp, and Wedel (1998) suggest that "hard laddering" such as APT is a recognition task, whereas traditional "soft laddering" is a recall task. Further, it is posited that recall could lead to fatigue and boredom, and thus "unwanted cognitive responses" (Grunert and Grunert, 1995). This conclusion, given the level of involvement in an in-depth interview compared with the task of marking cells in a matrix, seems highly questionable. In fact, the exact opposite may well be true. Research experience suggests that forcing respondents to think critically about their responses produces more meaningful data (Reynolds, Dethloff, and Westberg, 2001).

4. Analysis of "hard" MEC data: Analysis of APT data to determine the significant linkages between codes from the implications in the HVM assumes independence. With APT, a consequence-value connection is assessed independently of its origin, the attribute-consequence connection. However, a probability indicative of the strength of the connection between the codes at adjacent levels is provided, which is adjusted for response tendencies. The resulting data are represented in the resulting HVM, with the largest probabilities defining the strength of the connecting linkage.

Research that focuses on the convergent validity of these two methods (Hofstede, Audenaert, Steenkamp, and Wedel, 1998), "soft" laddering and the "hard" APT method, for the same categories reveals differences in the frequencies of the codes obtained (which is attributed to the difference in task orientation as detailed earlier). [However, the testing of the assumption of conditional independence between A-C and C-V suggests that the APT methodology of gathering the data in separate steps is supportable. The authors also note that when the frequencies of codes are adjusted, the structural differences (strength of the linkages) are not statistically significant between the two methods.] Yet, two questions remain. First, given the task-related differences, which method provides more reliable and valid results? [As will be detailed later, only the output from "soft" laddering has provided support for the validity of MECs derived in this way, by demonstrating the additional contribution of the higher levels of abstraction with respect to preference evaluation (Jolly, Reynolds, and Slocum, 1988; Reynolds, Gutman, and Fiedler, 1984).] Second, in terms of interpretation as input to the strategy development process, to what degree do the two approaches of deriving the HVM (comprised of both content and structure) result in similar conclusions?

5. Market research MEC segmentation: The market research orientation of APT has been extended to address the segmentation issue, using as an example different countries with the same product categories
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(Hofstede, Steenkamp, and Wedel, 1999). An integrated analytical model is applied that yields both the MEC segments (which can be mapped separately) and estimates of the country-specific segment percentages. For additional understanding, the resulting segments are contrasted to descriptor data, including a range of traditional inventories (e.g., sociodemographics, media consumption, attitudes). Interestingly, the output of this probabilistic analysis is contrasted to a deterministic alternative, K-means cluster analysis (Wedel and Kamakura, 1998). Significantly different results were obtained using the different analytic methods. The authors conclude that their analysis is superior, primarily due to the fact that the clustering analysis does not take into account differences in response behavior, meaning that the resulting maps for their method produced noticeably different HVMs for each segment. The same limitations noted in item 4, in terms of levels and meanings of the concepts presented (probably more so for the latter given the international context), applies to this extension. Of course, without translation of the findings with respect to resolution of the marketing problem, it is difficult to assess the actionability of either analytic method.

In sum, the efficiency arguments of time and money for conducting large scale, means-end marketing research versus the traditional “soft” methods involving one-on-one interviewing are appealing. However, the trade-off is difficult to evaluate, given that four levels are required for actionability with respect to the development of positioning strategy, and no research extending the APT framework to this problem domain is available.

The second means-end consumer research stream moves from developing general category maps, which is the marketing research orientation, to focusing on brand choice grounded in a decision context as the basis upon which MECs will be obtained. To achieve this, the MECs that are obtained must be initiated from a competitive preference- or consumption-based contrast [i.e., why one’s favorite brand A is consumed (in a specific situation) more than one’s second favorite brand B]. As mentioned earlier, research that contrasts perceptual differences to preference differences using the means-end elements has demonstrated that the higher levels of abstraction come into play only with respect to explaining preference (Jolly, Reynolds, and Slocum, 1988; Reynolds, Gutman, and Fiedler, 1984). Given this finding, and the fact that understanding brand choice is fundamental to the development of marketing and specifically positioning strategy, the critical directional focus becomes one of developing MECs based on the brand-derived “choice-discriminating” distinctions—necessitating moving from category maps (HVMs) to choice-specific maps (Customer Decision Maps or CDMs).

6. MEC self-report segmentation: Prior research efforts have attempted to address the MEC segmentation issue in a two-step process. Vanden Abeele (1992) first derived summary ladders, and in a second phase of the research had respondents evaluate complete ladders, thereby classifying themselves into segments. Similarly, Reynolds and Rochon (2001) first identified segments from a laddering study and then converted each ladder into descriptive narratives. In the second phase of this research, respondents were sensitized by rating the importance of the relevant consequences in the category. Then, they were presented the descriptive statements reflecting the ladders and asked to identify which two were the most representative of them. Both of these attempts at segmentation suffer from the limitations of predetermined ladders and the potential for response bias from the self-reporting component of the methodology.

7. Decision framing: Olson and Reynolds (2001) suggest that a marketing problemsolving research orientation must fulfill two requirements. First, the marketing problem must be framed as a specific decision made by specific groups of consumers. Second, to increase actionability, managers need to know exactly what is driving consumer decision making (by key target groups). The process of framing the marketing problem into a research problem, defined in terms of consumer decision making, involves answering the following four questions:

a. Who are the relevant consumers or customers whose decisions I need to understand (e.g., “brand A loyalists versus competitive brand loyalists,” “heavy users versus light users,” “undecided voters versus base supporters”)?

b. For those consumers, what particular behaviors or actions (shopping, brand choice, or consumption decisions) are most relevant to my marketing problem (e.g., brand purchase, joining sales organization, donating money)?

c. What are the social and physical contexts in which those behaviors or actions occur (e.g., time of day, relevant others involved, economic constraints)?

d. What choice alternatives does the consumer consider when making the key decisions in those situations (e.g., brands in the choice set, candidates in the election, alternative job opportunities)? (See Olson and Reynolds, 2001 for a complete explanation of these framing questions.)

The box in the upper right of Figure 1 highlights three standard questions that provide a choice-based distinction from which MECs may be obtained. A behavioral question with respect to Trend asks
The development of a segmentation approach, using choice-based MECs developed for key samples, offers the marketer an added level of knowledge that can be extremely valuable in prioritizing the strategy development process, as well as in media strategy.

The respondent if he or she is consuming more or less of a given product over some time frame (e.g., six months). If the respondent's behavior is different (some degree of more or less), then the distinction obtained is a result of the Why (more or less) question. With respect to Consumption, the respondent is asked why he or she consumes/purchases one brand over another (oftentimes within a particular context). The “On the Margin” distinction is obtained by first asking the respondent where he or she is on a numerical scale (e.g., satisfaction, likelihood of purchase, or voting for a particular political candidate). Then, using the initial numerical response as the basis, the respondent is usually asked two more questions: (1) “what is the barrier to moving you one point higher on the scale (i.e., more likely to vote for a candidate)?” and (2) “what is the reason that you did not rate your likelihood lower?” Using a key-discriminator approach such as this, for either brands or political candidates, one answer represents “equity” and the other “disequity.” These choice-driven distinctions then serve as the basis of the laddering and subsequent brand equity analysis by consumer group.

Question framing, then, provides the sample specification that is most meaningful to the problem. The questions outlined above focus directly on understanding the motivating basis of choice, by obtaining the MECs through “soft,” qualitative laddering methods that correspond to the key choice distinctions the consumer is making. The number of ladders required in this approach is usually no more than four, and given their precise definitions, can be obtained in less than 20 minutes of interviewing time. This translates into a total interview time of 30-35 minutes, which is significantly shorter than more general laddering interviews, which often take 90 minutes. Thus, the design specificity of this “understanding discriminating choice” approach provides much greater research efficiency, while at the same time yielding information directly related to solving the marketing problem. Given the highly focused design aspects resulting from problem framing, the use of the internet for interviewing becomes a distinct possibility to gather MEC data, thereby addressing much of the cost limitations associated with traditional laddering research.

8. MEC decision equity analysis: Analysis of the results from MECs constructed from choice distinctions provides the researcher another set of data, in addition to the CDM. Equities and disequities (stemming from the specific distinction) can be determined and quantified with respect to the elements of the ladders for designated segments. Simple percentages contrasting equities and disequities for each code can be developed for the key sample groups, which can then be combined with the CDM to provide additional focus for the strategy development process (Reynolds, Dethloff, and Westberg, 2001). To illustrate, consider the research issue of developing political strategy where there are usually only two choices. Given that the Undecided voters (individuals in the center of a bipolar scale anchored by the candidates) are critical to developing a winning strategy, one requires knowledge of both the equities and disequities for these Undecided voters with respect to each candidate. The strategist’s question this answers, then, is how to move them toward the desired candidate by reinforcing the positives and supplanting the negatives for the desired candidate (positive advertisements) and emphasizing the negatives for the opposition (attack advertisements). This equity-disequity analysis framework permits strategy specification that directly corresponds to the decision structures of the key voter target group.

9. Decision segmentation: The development of a segmentation approach, using choice-based MECs developed for key samples, offers the marketer an added level of knowledge that can be extremely valuable in prioritizing the strategy development process, as well as in media strategy. Consider the political example mentioned above. If one knew the composition and size of the decision clusters for the undecided voters, developing both the positioning strategy(s) and the corresponding media weights would be all the information required (if Undecideds were the only consideration). For a brand marketing example, consider light beers. If one would sample loyal users of competitive brands and then develop MECs based upon a consumption distinction (which yields an equity for the “loyal” brand and a disequity for the “second choice”), contrast this equity information in combination with segments would provide a detailed,
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concrete basis to determine the optimal positioning. Thus, the potential value of such a segmentation methodology for decision-based MECs appears highly significant.

The research question is how to determine homogeneous decision hierarchies from qualitative data that can define the segments. Given that complete ladders, which are of varying lengths, are the fundamental unit of analysis, the research problem can be defined as akin to clustering, with special considerations stemming from the nature of MEC data. The following section briefly reviews prior research on segmentation approaches to MEC data, beyond the probabilistic approach applied to APT data (Hofstede, Audenaert, Steenkamp, and Wedel, 1998) described earlier, and summarizes the analytical problem of developing an optimal methodology.

MEC SEGMENTATION METHODS

MEC theory has been proposed to be an ideal form of market segmentation, in that it avoids the inferential process required when one uses traditional segmentation techniques (Reynolds and Gutman, 1988; Valette-Florence, 1998). The initial problem with implementing the MEC framework to segmentation is that the CDM only displays respondents' aggregate decision structures and they cannot be assigned to a specific decision network cluster. To address this fundamental problem of utilizing qualitative MEC data as the basis of a segmentation methodology, a series of recent methodological approaches have been suggested. These approaches will be briefly reviewed, with the goal of highlighting the critical underpinnings required for the development and refinement of an optimal MEC segmentation methodology.

In addressing the MEC segmentation problem, Valette-Florence and Rapacchi (1991) utilize a combined correspondence analysis and clustering model, using the individual code elements as the units of analysis. This approach, by virtue of the fact that only summary measures of association are used, fails to take the combination of linkage strengths across the elements directly into account, which misses capturing the uniqueness of this type of data sequencing across the entire MEC.

Recognizing the need to change the unit of analysis to the entire MEC, Aurifeille and Valette-Florence (1995) propose a decision segment identification method that assigns the obtained ladders in the data set to a list of all possible ladders, based upon deriving a Euclidean metric computed across all the elements in the ladder. Their multistep clustering approach to obtaining segments requires several arbitrary choices to be made by the researcher, making it difficult for other researchers to evaluate and, most importantly, independently replicate.

Cognizant of the need to create a more standard analysis methodology, Valette-Florence (1998) suggests another research approach to identify segments within MEC data. This approach utilizes the optimal scaling features of nonlinear generalized canonical correlation analysis, seeking to explain the interactions (in the case of MEC, the implications) between the codes contained in the ladder. The output from this analysis is combinations of code elements that represent clusters, which are then used as a basis to assign ladders. A review of their example output of codes that represent a decision cluster reveals that a significant number of codes within a level are typically present. That is, five or six different consequences, for example, can be present in a given cluster. This representation of the laddering data fails to capture the essence of one common ladder, with elements present from all levels, thereby making it more easily understood—and more appropriate for use in strategy development.

Although this methodology does compute linear indices of goodness-of-fit, it seems more appropriate to simply derive a measurement of internal consistency directly from the implications, which reflect the true nature of the qualitative data.

Continuing this search for a methodology that determines optimal decision clusters from MEC data, Poulsen, Juhl, and Grunert (1995) suggest using Latent Class Analysis. Their approach also begins with the enumeration of all possible ladders and proceeds to compute a conditional probability for each ladder in the data set, with regard to the set of possible ladders. The clusters are then determined by selecting the highest conditional probability. The somewhat concerning result of using this method, based upon conditional probabilities, is that the key elements that define the cluster segment may not be present in any one ladder in the data set. Though this approach is quite reasonable, the notion that a probabilistic model is required, when a simple, deterministic-matching methodology based upon the actual MEC data should be possible, seems to unduly complicate the research problem. Moreover, the fact that the actual ladders are used as the basis of any deterministic method virtually assures that the resulting method virtually assures that the resulting method will be isomorphic to the MECs in the raw data.

A review of the highlighted summary comments noted above yields the directional requirements that define what would be a desirable solution to the segmentation of MEC data:

1. The appropriate unit of analysis is the entire MEC.
2. The analysis procedure should be standardized, minimizing the number of decisions the analyst is required to make.
3. Each resulting cluster should closely reflect one decision orientation.
4. All statistical measures should be based upon the number of implications between the MEC codes as the metric of variance.

5. A deterministic model capable of identifying internally consistent MEC segments that fit the nature of the data, particularly with respect to their subsequent interpretation, is preferable.

To develop a deterministic solution for the clustering problem of MEC, the following fundamental methodological issues must be resolved:

- how to ensure the decision segments are as independent as possible, and given the overlapping nature of decision networks (multiple meanings derived from a common decision element), will permit some degree of common codes;
- how to determine the optimal group of ladders that should be included in a given decision segment;
- how the internal consistency of the resulting decision clusters is to be quantified; and
- how to assess the independent contribution (implications accounted for) of each cluster, and for combinations of clusters that define alternative solutions.

In the following section, the specifics of this new, deterministic approach to segmenting MEC data, termed Decision Segmentation Analysis (DSA), will be detailed. The hypothetical example data set for light beer (Figure 2) will be used to illustrate the DSA model, and results from an analysis of political research MEC data from the 2004 U.S. presidential election will be presented. Central to this exposition will be the translation of the research from this consumer choice-based approach to the optimization of positioning strategy.

**DECISION SEGMENTATION ANALYSIS (DSA)**

The deterministic identification of which decision clusters or common pathways exist in MEC data simply involves setting three values: (1) a minimum threshold value that defines the initial level for significant implications to be included in a given MEC (default of 10), (2) the number of desired clusters in the solution (2–9), and (3) the maximum number of codes that may be included in a chain (4, 5, or 6) (see Appendix A for a detailed outline of the clustering analysis procedure).

The hypothetical data set (Ladders = 108) that generated the CDM in Figure 2 (cutoff level of four direct implications) was analyzed with DSA. To provide for an evaluation of solutions, analyses were specified as (1) minimum threshold level of 10, (2) 3–5 cluster solutions, and (3) the maximum number of codes within an MEC cluster at 4, 5, and 6. Table 2 is a summary of the percentage of ladders accounted for in each of the solutions. The DSA summary presented above noting the percentage of ladders accounted for by each combination of Maximum Chain Length by the Number of Clusters in the solution readily permits the determination of the optimal solution. A review of this summary reflecting the percentage of ladders accounted for by a 4-element MEC solution suggests that the addition of a fifth cluster does not account for a significant increase in ladders (only 4–63 percent to 67 percent), suggesting that a four-cluster solution is appropriate with a maximum MEC length of 4.

<table>
<thead>
<tr>
<th>Cluster Number</th>
<th>Maximum Chain Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solution</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>51%</td>
</tr>
<tr>
<td>4</td>
<td>63%</td>
</tr>
<tr>
<td>5</td>
<td>67%</td>
</tr>
</tbody>
</table>

A summary of the light beer CDM, including the decision segments (and their respective percentages), appears in Figure 3. Note there are two additional differences beyond the segmentation: the positioning of the codes in the map and the noting of nonsegment lines by the dotted connecting lines. Importantly, once the underlying decision segments are known, this information can be used to...
construct the CDM, with a goal of “simple structure”—arranging the codes in the map such that the connecting segments are as vertically oriented as possible. The general organization of the map is much simpler and easier to interpret once the information regarding the decision segments is used as a basis for organization. Of course, a significant increase in interpretability also results from specific knowledge of the dominant pathways of the decision segmentation. This point is reinforced by the nonshaded codes, the ones not included in any segment, and the dotted lines, which represent connections that were present in the original CDM that may now be viewed as an artifact of the manner in which traditional HVMs are constructed.

To illustrate the key DSA statistics, consider the summary implications (direct/indirect) for the first segment in Figure 3 (see Table 3). This segment accounts for 22 percent of the ladders (%L). Chain strength (CS) is the average total of connections, both direct and indirect, across the pairs of codes. And, internal consistency (Q%) indicates the percentage of the implications of the ladders in the segment contained in this common set of codes is 84 percent.

There are several key points to be outlined regarding the DSA of this example data set. First, the effect of the starting point (the specification of a threshold value) appears to have a minimal effect. Second, the exact composition of a decision cluster is identified, which of course may include common (overlapping) codes. (It is further conjectured that overlapping codes would have a deleterious effect on analysis using a linear model.) Third, the assignment of MECs to a given cluster or decision segment provides a basis for subsequent analyses with external variables. Fourth, the quality of “chain strength” and the number of implications accounted for provide a direct measure of the variance accounted for in the solution. Fifth, and perhaps most importantly, DSA methodology attempts to focus on the increased understanding and interpretability of MEC data. The ability to utilize multiple configurations of threshold, number of segments in a solution, and the

\[
\begin{array}{cccccc}
\text{Code} & 101 & 201 & 204 & 301 & 401 \\
101 & \text{Less calories} & 14.00 & 0.02 & 0.08 & 0.12 \\
201 & \text{Not gain weight} & - & 6.00 & 10.02 & 0.16 \\
204 & \text{Relax} & - & 6.00 & 0.06 \\
301 & \text{Coping/reparative} & - & 8.06 \\
401 & \text{Self-esteem} & -
\end{array}
\]
maximum number of codes to be included in the chains, combined with a set of summary statistics to evaluate the solutions, permits the comparison of solutions to identify the most stable.

**DSA OF POLITICAL DECISION MAKING (DIS)EQUITIES**

To demonstrate the potential of DSA to provide a basis for understanding the key aspects of decision making with regard to political choice, it was applied to ladder data gathered as part of a larger study conducted prior to the 2004 national presidential election. The study was conducted by a professional research company that specializes in laddering research, at a central location with prerecruited respondents. Respondents were screened on the basis of five factors: (1) voted in the last presidential election, (2) intend to vote in the upcoming presidential election, (3) voting intention (likelihood of voting for a particular presidential candidate), (4) age, and (5) gender. Factors (3)–(5) were balanced across the N = 72 sample (with the age split at 40). A series of other questions dealing with issues, leadership traits, media behavior, and demographics were also part of the research instrument. The average time for the one-on-one interview was 35 minutes.

Voting intention (3) was defined as follows:

- definitely Kerry
- most likely Kerry
- leaning toward Kerry
- undecided
- leaning toward Bush
- most likely Bush
- definitely Bush

(Disequity) Ladders were generated using the voting intention response (3) as an anchor by asking the respondent the following question for each presidential candidate, Kerry and Bush:

What is the single most important thing—a position on a specific issue, or a leadership trait—that if changed about (candidate), would make you more likely to vote for him?

This framing of the What question in this way attempts to identify the specific, discriminating “disequity” that would offer the largest potential to affect the voting decision. (The “definitely” group for both candidates was not asked the question regarding their candidate for obvious reasons.) Laddering was conducted to obtain the Why answer, using this disequity distinction as the starting point. After coding the MECs, it was determined that 66 percent of the resulting ladders were complete chains (i.e., they had at least one code element at each of the four levels).

**Results**

The default initial threshold of five (accounting for just above 50 percent of the total implications) was used. A series of cluster solutions were run across all combinations of the number of segments (2–7) varying the maximum number of codes included in a chain (4, 5, and 6) separately for the disequity ladders of Kerry (L = 61) and Bush (L = 62). A two-segment solution was determined optimal for Kerry and a three-segment solution for Bush. The summary statistics for the resulting decision segments and the composite CDM answering the Why question are presented in Figure 4.

The percentage of ladders accounted for by the DSA solutions is noticeably different, 52 percent and 72 percent, for Kerry and Bush, respectively, indicating more idiosyncratic decision structures for the disequities for Kerry. This perception is reinforced by the relatively low internal consistency measure for the second Kerry segment (Q% = 44) and the lower average of connection strengths (CS = 2.7). (It should be noted that this measure is negatively biased, in the sense that having two attributes in the chain constrains the number of implications.) It is worth noting that, given the myriad of issues that could drive political choice, the fact that a relatively small number of decision segments could be identified by this deterministic methodology lends strong support for this approach.

The deterministic structure provided by DSA (Figure 4) makes the construction and subsequent interpretation of the CDM much easier, with less inherent subjectivity in the overall research process, as well as avoiding the ambiguity created by the evaluation of probabilistic relationships. In this case, the five clearly delineated decision segments, which necessarily avoid the interpretive confusion created by those codes and their connecting linkages not in the segments, permit an unambiguous interpretation of the resulting CDM. Note-worthy is the fact that there is substantial overlap of codes between these decision segments at the psychosocial consequence and value levels in this example, which is not generally the case in product/service marketing research.

**Strategic interpretation**

The development of political strategy using the means-end framework has previously involved combining MEC mapping with polling data (Wirthlin, 2004, p. 142). The DSA approach, when used in conjunction with the disequity question format, both minimizes map interpretability issues and provides additional insights into the framing of strategic options. In the case of political data, the same data and analyses would be done regardless of candidate. For example, if you were the Kerry strategist, you would interpret the Kerry disequity segments as the basis to construct positive issue communications, thereby minimizing the negative barriers. And,
you would develop attack communications focusing on the Bush disequities, essentially reinforcing the negatives (with the reverse being true if you were the Bush strategist). Importantly, the practical application of DSA for political strategy development would focus on the Undecided voters, rather than all voters (as in this case), which would require a significantly larger sample.

This example, though from a small sample, demonstrates the potential of this decision segmentation approach to give clear direction for the strategy development process—specifying strategy based upon the dominant MECs. Specifically, the fact that the decision segments are identified with their critical positioning component at the psychosocial consequence level (Olson and Reynolds, 1983), along with the accompanying verbatim from the laddering, provides the strategist with an efficient methodology to develop strategy. The applications of this approach to segmenting, and thereby understanding key customer groups (i.e., “brand loyal vs. competitors’ brand loyal”) and their underlying equities and disequities in developing marketing strategy and positioning, appear to have significant potential.

**SUMMARY**

For an organization to be truly market-driven, the fundamental orientation of marketing management must be completely customer-driven in its view of the competitive marketplace. Not only do customer needs frequently change, requiring different product/service offerings (and corresponding positionings), the competitive marketing environment is always changing, and the resulting interpretation of these market forces of change that underlie the development of strategy must be understood as fully as possible.

Traditional segmentation methods that serve as a basis to understand strategic equity of a brand franchise with respect to the competition incorporate a combination of segment-defining characteristics, such as demographic, psychographic, attitudinal, and behavioral measures. These approaches to defining homogeneous customer groups require the marketer to infer the underlying decision processes of each segment, which leaves in question the motivational, explanatory reasons underlying changes in the marketplace. Recognizing the potential of gaining a more in-depth understanding of the consumer, marketing researchers have adopted means-end theory as a conceptual framework. In order to gain efficiencies in terms of cost and timing, market researchers have developed “paper and pencil” methods to elicit means-end cognitive structures, as opposed to the standard in-depth interviewing methods. The methodologies they suggest raise several issues; the most important being the failure to focus on decision making underlying brand choice as opposed to simply a cognitive (association) structure model. A
The applications of this approach to segmenting, and thereby understanding key customer groups (i.e., "brand loyals versus competitors’ brand loyals") and their underlying equities and disequities in developing marketing strategy and positioning, appear to have significant potential.

review of the evolution of means-end research, from the original cognitive orientation to the market researchers’ adaptation to the more recent decision-based extension, is provided.

It is noted that the decision-based focus of gaining consumer understanding using traditional laddering has clear advantages in terms of the strategy development because of its ability to (1) provide a comprehensive consumer lexicon and that (2) incorporate all four levels of decision making that define the basis for defining a complete strategic positioning in consumer terms. Heretofore, however, the one key advantage of the marketing research translation and implementation of means-end theory, beyond the cost implications, is the ability to undertake market segmentation. This article introduces a new analysis model to be applied directly to MEC data obtained from traditional laddering methods, termed Decision Segmentation Analysis, which directly addresses this previous shortcoming. An example of DSA with hypothetical means-end data is detailed to explain the potential of the technique. It is noted that one additional benefit of this approach to all means-end research is the ability to standardize the construction of summary decision maps by the elimination of spurious elements/codes and by using the segments to define a simple structure format for map construction. In addition, an empirical example is presented, bridging to application for strategy development in the political domain. In sum, it is demonstrated that if a marketing or positioning problem is framed in decision terms, identifying segments in this manner provides a very solid foundation for optimizing the strategy development process.

To expand this idea of framing a problem in terms of understanding decision making, consider the following types of example marketing issues and questions to which DSA could be readily applied.

- **Brand/Service Loyalty: Brand A versus Brand B**
  What are the decision equity segments (and corresponding disequities) of the respective brands?

- **Store Loyalty: Store A versus Competition**
  What are the decision equity segments that drive customer loyalty for my store?

- **Rx Prescriptions (for MDs): Brand A versus Brand B versus Brand C**
  What are the decision equity segments underlying brand loyalty for writing prescriptions?

- **Channel Loyalty: Preferred Organization versus Second Alternative**
  What are the decision equity segments that make my organization preferred?

In sum, segmenting consumers, by identifying the underlying basis of brand/store/candidate/issue differentiation in terms of their decision-making processes, yields a form of market segmentation that answers both the What and Why questions required to optimize brand strategy development.

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REFERENCES


DETECTION SEGMENTATION IMPLICATIONS


APPENDIX A

DSA examines a set of coded ladders, determines the primary MECs (seed chains), and then assigns ladders to each. The analytic steps to develop seed chains are:

1. **Implication threshold.** This represents a minimum number of connections between codes, both direct (adjacent) and indirect (nonadjacent), that defines a significant pairwise connection. A default value is the level at which 50 percent of the total direct connections would be accounted for.

2. **Potential four-level seed chains.** A list of all significant code pairs is constructed by combining the pairs of pairs that meet the implication threshold. In the case of redundant codes (i.e., a common code in the pairs), which results in only three different levels being represented, a fourth code is added on the basis of maximizing "chain strength," defined as the average number of direct and indirect implications represented in the four-level chain. All duplicates are removed. (If desired, the number of potential seed chains can be limited by a series of filtering statistics.)

3. **Determine optimal seed chains.** A stepwise analysis, based upon (a) the amount of new implications provided and (b) limited by the amount of overlap permitted between existing chains in the solution, is performed with a maximum of nine clusters. (The default value of one overlapping code between chains may be overridden.)

Once the seed chains are determined, the assignment of MECs is done as follows:

4. **Inclusion criterion.** In order for a MEC to be assignable, it must meet one of the following two conditions: (a) match three or more codes or (b) match at the psychosocial level and either the attribute or functional consequence level. (The relative importance of the psychosocial level for understanding the leveragability and uniqueness of a particular positioning is the reason why it has a higher role in the segmentation process.) MECs that do not satisfy these requirements are not assigned (at this time).

5. **Tie breaker.** In the event an MEC is assignable to more than one cluster, the following sequence of tests is applied: (a) number of code matches; (b) weighted score of matches (4 = psychosocial consequence, 3 = functional consequence, 2 = attribute, and 1 = value); and (c) seed cluster with the highest "chain strength." (These weights of the levels correspond to the rank order of relative importance of the levels, in correlating with affect for the product [purchase intent] derived from 125 advertising assessments.)

Once the four-level seed chains and the ladders are assigned, an option to add additional codes to the seed chains is available.

6. (Optional) **Expanding codes in seed chains.** A maximum number of codes can be set as the number of codes in a seed chain (4, 5, or 6). For the maximum of 5 and 6, then, the largest code not in the seed chain is determined and assessed to see to what degree it decreases overall chain strength (the default value is 5 percent). If an additional code exceeds this threshold, it is not added.

7. **Reassignment of ladders to new seed chains.** The addition of the new code to the prior seed chains requires all the ladders to be reassigned using the same rules from above.

The two key statistics above are the number (percent) of ladders assigned to each segment and "chain strength," which is a measure of quality (average number of implications across all pairs of connections in the overall data set). After the analysis is completed, a third measure reflecting the internal consistency of the ladders within the segment is computed. This measure is the percentage of implications (variance) accounted for by common codes within the chain for the ladders within a given segment. DSA may be viewed as a clustering technique specific to the nature of MEC data, particularly considering the relative importance of levels for understanding consumer choice.