A maximum difference scaling application for customer satisfaction researchers

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This paper puts forth maximum difference scaling as a valid research method to determine attribute importance for customer satisfaction research, which in turn can drive valid and meaningful need-based segments of the marketplace. In addition, this paper empirically demonstrates the value of bringing need-based segmentation into the centre of customer satisfaction analysis. The results suggest that implementing maximum difference scaling to determine attribute importance scores for the overall market, as well as to create valid need-based segments, will result in significantly different improvement priorities as compared to more traditional customer satisfaction approaches.

Introduction

The marketing literature has stressed the importance of understanding customer needs and satisfaction, along with understanding these concepts for each market segment (Kotler & Armstrong 2006). Once segments are effectively understood, firms can customise their offering to maximise segment satisfaction (Freytag & Clark 2001). Kaplan and Norton (1996) state that strategy requires a clear articulation of targeted customer segments, their needs and wants, along with a value proposition required to attract, satisfy and retain targeted customers. They suggest that defining a unique value proposition for a targeted market, one that satisfies their unique needs, is the single most important dimension of strategy (Kaplan & Norton 1996).

Best practice in market segmentation suggests that researchers identify segments based on customer needs or benefits sought (Bennion 1987; Griffith & Pol 1994; Freytag & Clark 2001). While the advice to
segment markets on needs and benefits has been prevalent for quite some time (Bonoma & Shapiro 1984; Haley 1985), Best (2004) argues that many firms fall into the demographic trap when segmenting markets – segmenting markets first and foremost using demographic variables. Unfortunately, segmenting markets based on demographic variables severely limits understanding of customer needs, yet this approach tends to be common in practice.

The literature on market orientation has long advocated the importance of customer satisfaction in attracting and retaining customers (Garver & Cook 2001). In addition, customer satisfaction is a key objective associated with Total Quality Management and Six Sigma strategies. As a result, firms have embraced customer satisfaction as a driver of business strategies, often including this concept as a key organisational objective (Gale 1994; Woodruff & Gardial 1996). Not surprisingly, customer satisfaction research is the most popular form of market research conducted today (Garver 2001).

Recently, Garver et al. (2008) suggested that researchers would better understand their employees and customers if they formed need-based segments on attribute importance, and then examined perceptions of segment satisfaction. These authors suggest that analysing only the overall marketplace will likely hide and obscure significant differences among segments for both attribute importance and satisfaction. Marketers have stressed the importance of segmentation for decades, yet the focus of most satisfaction research tends to take an overall perspective, or one driven by demographic segments only (Garver et al. 2008).

As the implementation of customer satisfaction research continues to increase, researchers have identified a number of issues with traditional methods employed by customer satisfaction researchers (Brandt 1998; Chrzan & Golovashkina 2006). For example, Garver (2003) has raised serious methodological issues associated with traditional approaches for determining attribute importance. Cohen (2003) suggests that given the limitations of traditional importance rating methodologies, effective market segmentation is simply not feasible. To solve this problem, Cohen and Orme (2004) put forth maximum difference scaling as a feasible alternative to generate importance data that are more accurate and suitable for segmentation analysis. Chrzan and Golovashkina (2006) empirically examine a number of traditional research methods for identifying the importance of product and service attributes, and suggest that maximum difference scaling is the most accurate and valid research method available, further suggesting that the data are ideal for segmentation analysis.
The purpose of this paper is to put forth maximum difference scaling as a research methodology that brings need-based segmentation into the centre of customer satisfaction analysis. Specifically, this paper will address the following critical questions.

- Will maximum difference scaling generate significantly different attribute importance ratings compared to traditional methods?
- Using maximum difference scaling importance data as a key input of satisfaction analysis, will different improvement priorities arise as compared to traditional methods?
- Employing need-based segmentation within customer satisfaction analysis, will improvement priorities be different compared to improvement priorities for different segments?

To answer these questions, this paper will put forth maximum difference scaling as a research tool to capture attribute importance scores, which, in turn, allows satisfaction researchers to identify need-based segments. To accomplish this purpose, an overview of the customer satisfaction and market segmentation literature will be discussed, highlighting key issues and gaps. Then, an overview of maximum difference scaling will be presented, along with specific applications for combining segmentation analysis and customer satisfaction research. Research data will be examined with traditional methods, which will then be compared and contrasted with maximum difference scaling.

**Literature review**

The literature review will examine attribute importance analysis, need-based segmentation and maximum difference scaling.

**Identifying attribute importance**

Practitioners want to know what attributes are most important to their customers so that they develop strategic and tactical plans that are aligned with the needs of their customers. For example, if technical support is the most important attribute to customers, then the firm would likely want to excel in this area, making technical support a competitive advantage. Attribute importance analysis is key to strategic planning and a primary input into quadrant analysis (Martilla & James 1977; Swinyard 1980; Hawes & Rao 1985; Myers 2001).
Chrzan and Golovashkina (2006) discuss a number of alternative methods to measure attribute importance, such as Q-sort, unbounded ratings, magnitude estimation and constant sum, yet these methods are seldom employed by satisfaction researchers due to their implementation and analysis limitations. Customer satisfaction researchers have traditionally employed both stated importance analysis as well as statistically inferred research methods to address attribute importance (Garver 2003). Thus, these two methods will now be discussed.

Traditional stated importance ratings
Customer satisfaction researchers often use stated importance ratings to measure attribute importance (Oliver 1997). To implement this technique, researchers ask survey respondents to rate the importance of each customer satisfaction attribute, typically ranging from ‘not important’ to ‘critically important’. Although commonly used in practice, this method has major limitations (Garver 2003; Cohen & Orme 2004; Chrzan & Golovashkina 2006).

The most significant limitation is that stated importance ratings often display a lack of discriminating power between customer satisfaction attributes (Cohen & Orme 2004). In many applications, all attributes are ‘critically important’ to customers. Cohen (2003) also demonstrates that this method is flawed, again showing very little discrimination between attribute importance scores. If all attributes are found to be ‘very important’, then the research findings are extremely limited.

As a result of this problem (i.e. poor discrimination), segmentation analysis is severely limited. Because everything is important to customers, segmentation analysis typically uncovers segments that are driven by response method bias patterns rather than valid attribute importance scores (Cohen & Orme 2004). As a result, market segmentation (need-based segments) rarely occurs with this technique (Cohen 2003).

Statistically inferred importance ratings
To overcome the problems of stated importance analysis, many customer satisfaction researchers employ statistically inferred importance ratings, even though this method also has numerous limitations (Oliver 1997). Implementing this technique, researchers regress or correlate attribute satisfaction ratings against overall satisfaction to determine attribute importance ratings (Woodruff & Gardial 1996).

Chrzan and Golovashkina (2006) suggest that this method also has significant limitations. Customer satisfaction researchers typically use
multiple regression or structural equation modelling to determine attribute importance ratings. These statistical techniques assume the following: (1) the data have a normal distribution; (2) the statistical relationship variables are linear; and (3) that modest levels of correlation exist among independent variables (Garver 2002). These assumptions are almost always violated in customer satisfaction research, causing interpretations from attribute importance analysis to be suspect (Chrzan & Golovashkina 2006).

Traditional regression analysis does not allow the researcher to derive customer-level attribute importance ratings, because these techniques produce beta coefficients for the population as a whole. As a result, segmentation analysis is not possible because beta coefficients are not generated for individual customers. Advances in latent class regression analysis overcome this problem, suggesting that latent class regression analysis may be a promising research method for employee and customer satisfaction researchers (Garver et al. 2008). It is important to note that the problem of high multicollinearity among customer satisfaction attributes remains a major limitation with latent class regression analysis as well.

**Need-based segmentation**

The marketing literature has long emphasised the importance of segmenting markets by customer need, to develop effective strategies (Kotler & Armstrong 2006). While this is clearly established as best practice, many firms fall short in this area. Best (2004) argues that many firms fall into the demographic trap when segmenting markets, suggesting that they segment markets first and foremost using demographic variables. Best (2004) suggests that firms should first form need-based segments (segments based on customer needs, benefits sought or attribute importance), then these segments should be described with the use of demographic variables. In this paper, need-based segments are synonymous with attribute importance segments.

Unfortunately, it is common practice for many customer satisfaction researchers and practitioners to gather satisfaction and loyalty data without concern for classifying customers into need-based segments. While researchers may do modest segmentation analysis with demographic variables (products used, size of customer, etc.), this is not analysing customer satisfaction via each need-based segment. This paper suggests that satisfaction researchers form need-based segments and then conduct customer satisfaction analysis for each segment. This issue – the lack of
need-based segmentation in customer satisfaction research – has not been adequately addressed in the literature, nor in practice.

It is important to implement need-based segments in customer satisfaction research because different segments will place varying levels of importance on different strategic attributes. For example, one software segment may place the highest importance on price and value, while another may place the highest importance on software performance and technical support. Clearly, these segments will respond differently to marketing strategies and will likely evaluate software vendors differently. For example, it is likely that the high-performance and technical support segment will have lower satisfaction with vendors who compete on price. In contrast, this same vendor will likely receive relatively higher satisfaction from the price and value segment. By not recognising different need-based segments, the results for these two segments may be ‘average satisfaction’, the resulting improvement priorities may be confounded and differences for each segment may not be recognised. This is an important limitation that needs to be recognised and addressed by researchers.

Why do most satisfaction researchers ignore need-based segments in their analysis? Current research methods for attribute importance analysis do not support this objective. As stated earlier, performing cluster analysis on stated importance ratings is often not feasible because there is not enough variation or discriminating power among attributes, not allowing need-based segmentation to occur within satisfaction analysis.

**Maximum difference scaling**

Maximum difference scaling is a relatively new research method that is receiving research attention from academic researchers and leading-edge practitioners (Cohen 2003; Cohen & Orme 2004; Chrzan & Golovashkina 2006). In this subsection, maximum difference scaling will be introduced, along with its advantages, limitations and typical applications. New applications for customer satisfaction researchers will be introduced.

**Overview**

Maximum difference scaling is an extension of the method of paired comparisons. Chrzan and Golovashkina (2006) suggest that, prior to maximum difference scaling, the method of paired comparison provided the most rigorous method to determine attribute importance ratings. With the method of paired comparisons, respondents are shown two items at a time and are asked to make a choice – so it is not a rating activity.
Whereas paired comparisons ask for only the best choice, maximum
difference scaling asks for both the best and worst choice from a
list containing multiple items. Employing maximum difference scaling
research questions, the respondent is typically shown four or five items
instead of just two items as with paired comparisons, with the task being
to select the most important (best) and least important (worst) items. The
researcher is able to discern a great deal of information from these two
choices (Cohen & Orme 2004). Using a four-item question, there are six
implied possible pairs. By selecting only the best and worst, five of the six
possible comparisons are answered. When faced with five items, maximum
difference scaling provides information on seven out of ten implied paired
comparisons. Maximum difference scaling is extremely efficient, resulting
in fewer questions and less respondent time, effort and fatigue.

While maximum difference scaling is quickly gaining popularity with
choice (pre-purchase) researchers, the technique is extremely versatile and
is starting to be used in a number of fields, including the post-purchase
environment.

Advantages over traditional customer satisfaction research methods

Maximum difference scaling has two distinct advantages over traditional
methods:

1. it is based on trade-offs with limited resources, a reality facing most
customers
2. increased variation in the data and more discriminating power among
attributes.

Maximum difference scaling has a number of advantages over traditional
research methods, one being that this technique forces customers to make
complicated tradeoffs in which respondents have to make difficult choices
(Chrzan & Golovashkina 2006). As stated earlier, it is quite common for
many respondents to state that everything is critically important. In surveys
of this kind, there are essentially unlimited resources and no constraints.
Essentially, respondents can ‘have it all’. This suggests that maximum
difference scaling is more aligned with the reality facing customers in the
marketplace, that respondents can not have it all and that resources are
limited in most instances. Customers make difficult choices and tradeoffs
every day, with limited resources, and maximum difference scaling is
aligned with this reality.
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Another important advantage is that the data display much higher variance, with more discriminating power as compared to traditional importance rating scales. A lack of discriminating power among attributes is a major issue associated with customer satisfaction research (Garver 2003). This is a major benefit of using maximum difference scaling and a driving force behind new applications in customer satisfaction research. As a result, the researcher is able to adequately discriminate among different attributes and is able to identify valid and meaningful need-based segments. The marketing literature has long discussed the importance of forming need-based segments, and maximum difference scaling is extremely effective at supplying valid data to accomplish this goal (Cohen & Orme 2004).

Research limitations
As with any research method, maximum difference scaling has limitations. The most significant limitation is the required time and effort on behalf of respondents. Chrzan and Golovashkina (2006) found that maximum difference scaling took the most time of any attribute importance methodology in their study. For example, maximum difference scaling took a median time of 171 seconds, while traditional importance ratings had a median time of only 38 seconds.

In addition to time, maximum difference scaling also requires more thought and mental effort than other methods. The choices respondents must make are often difficult and require concentration. As a result, it is easy to ‘burn out’ respondents, thus researchers must be careful not to overwhelm them. Both these limitations can also be viewed as advantages of this technique. Researchers suggest that the additional time and effort required on the part of respondents results in more valid and accurate data (Chrzan & Golovashkina 2006). While the choices may be difficult, understanding the task seems to be straightforward.

The data produced from maximum difference scaling are ratio-level data. The values are relative and are not absolute scores with an absolute zero. Similar to conjoint analysis data, specific importance scores can be evaluated only within a single individual study. If unimportant attributes are included in the research, then this may cause limitations for that study (Bacon et al. 2008). The identification of important and relevant attributes is the foundation of any valid research study, and it may be important to ensure that all attributes are relevant to study participants.

Maximum difference scaling choices require an experimental design where each attribute is shown in the exercise at least three times, with
each attribute being compared to different attributes each time. Some respondents feel that maximum difference scaling choices are redundant. From previous studies, some verbatim comments suggest that some respondents felt like they were answering the same question repeatedly.

Maximum difference scaling shares the same limitations as other stated research techniques. Many times, respondents overstate or understate the importance of some attributes in a research context relative to actual decisions. For example, price may be underrated in importance in a research context compared to spending money in an actual purchase. Related to this point, respondents may have various definitions and interpretations of the word ‘important’ (Oliver 1997; Garver 2003). Furthermore, it is important to specify the appropriate context of the exercise. For example, prior research has shown that respondents typically have different importance scores in a pre- versus post-purchase context (Woodruff & Gardial 1996).

**Applications for customer satisfaction researchers**

Maximum difference scaling applications will now be presented as a technique for customer satisfaction researchers. The focus of this section is to demonstrate the value of maximum difference scaling with need-based segmentation and importance analysis for customer satisfaction researchers. Specifically, we will address the following critical questions.

- Will maximum difference scaling generate significantly different attribute importance ratings compared to traditional methods?
- Using maximum difference scaling importance data as a key input of satisfaction analysis, will different improvement priorities arise as compared to traditional methods?
- Employing need-based segmentation within customer satisfaction analysis will improvement priorities be different compared to improvement priorities for different segments?

**Study context and methodology**

An industrial, high-tech company has collected customer satisfaction data for the last seven years, yet the research team was increasingly troubled by the results of attribute importance analysis. Originally, the research team used stated importance questions, yet the measures failed to adequately display variation and discriminating power – everything was
important. The research team also used statistically inferred importance measures. High levels of multicollinearity were present, thus the research team relied upon bivariate correlation analysis to determine statistically inferred importance ratings. Correlation analysis is not without limitations (Chrzan & Golovashkina 2006), yet the technique was determined to be the most appropriate given the data.

The research team was frustrated with its importance analysis. Attributes were receiving similar importance scores with relatively low variation, making it difficult to prioritise strategic initiatives and improvement opportunities. Furthermore, the research team was frustrated by its inability to segment the market other than by demographic variables.

The lead researcher put forth maximum difference scaling as an appropriate alternative and the management team supported the decision. To implement maximum difference scaling as part of the research process, the researcher implemented the MaxDiff program by Sawtooth Software 6.0. Traditional customer satisfaction ratings were captured in this survey, and the exact customer satisfaction attributes (24 attributes) were also entered into a MaxDiff experimental design. The customer satisfaction attributes represent all areas of their business from the customer’s perspective (product, technical support, customer service, billing, relationships, website, etc.). The MaxDiff design includes 14 trade-off questions with five attributes offered per choice. For each trade-off decision, the customer was shown five attributes and asked which attribute was ‘most important’ and which was ‘least important’.

In the original satisfaction research process, internal employees and customers placed the 24 attributes into six different factors or attribute indices based on the content of the questions. The lead researcher then conducted factor analysis with the attribute indices in mind. Factor analysis confirmed the attribute indices. Since that time, the firm has used these attribute indices to discuss and communicate results, along with overall loyalty. These exact same attribute indices will be used in this research, and include: (1) Partner; (2) Product; (3) Core Services; (4) Supplemental Services; (5) Value; and (6) Communication.

To identify improvement opportunities, the research team examined attribute importance scores and customer satisfaction scores simultaneously. A simple algorithm used in practice is to multiply the importance score by the difference between the total number of scale points and the actual satisfaction score (importance score \( \times (10 - \text{satisfaction score}) \)). The algorithm has a few interesting characteristics that warrant discussion. First, the difference between the total scale points and the satisfaction is
taken to guard against decreasing returns. Research has shown that top-box satisfaction leads to desirable results for the firm (Reichheld 1993), suggesting that an average satisfaction score of nine out of ten seems to be the mark of excellence and is the goal of leading-edge firms. However, trying to improve performance beyond this level may prove to be extremely difficult, resulting in a low return on investment (Jones & Sasser 1995). For example, many best-practice companies believe that moving average satisfaction scores from an 8 to an 8.5 may be much easier than moving from a 9.25 to a 9.75. By taking the difference between the total number of scale points and the actual satisfaction score, the difference becomes a fraction once the satisfaction score is beyond 9. As a result, the attribute improvement index will become increasingly smaller as actual satisfaction scores approach 10, or the total number of scale points. Interpreting this algorithm, the higher the score, the more priority should be given to that attribute. The improvement index is a relative gauge for identifying improvement opportunities, yet should be used in conjunction with a host of other important variables (Garver 2003).

An email invitation was sent to 1950 customers drawn randomly from the entire population to take a web-based survey that was password protected. A total of 612 customers responded to the survey, giving a response rate of 31.4%. The database was sorted to examine a particular customer group, which resulted in a final sample size of 241 customers. Comparing the sample characteristics to the population characteristics, the researchers felt confident that the sample was a good representation of the population. The MaxDiff fit statistics were extremely high, suggesting that the respondents were diligent and gave very thoughtful answers.

Employing Sawtooth Software, the data were analysed with hierarchical Bayes, then rescaled according to an algorithm within the software. Rescaled results from MaxDiff have a range from 0 to 100. With total scores for all attributes summing to 100, each attribute will display scores that are directly relative to other attributes in the study, with ‘more important’ attributes possessing higher scores. Once this analysis was conducted, the MaxDiff results were downloaded into SPSS and merged with customer satisfaction data for further analysis.

**Results**

First, a traditional customer satisfaction analysis will be presented. Then, results from maximum difference scaling, along with need-based segmentation analysis, will be presented in conjunction with the satisfaction
data. Finally, results from the different analyses will be compared and contrasted.

*Traditional customer satisfaction analysis*

Using bivariate correlation values for the attribute importance analysis, the results are included in Table 1 along with attribute customer satisfaction and improvement scores.

Examining the results from Table 1, *partner* has the highest importance score, followed closely by *product* and *core services*, which have relatively equal scores. *Supplemental services* and *communication* represent the lowest level of importance. Looking across all the attribute importance scores, they all display relatively low discriminating power, ranging from 0.70 to 0.53.

Examining the customer satisfaction scores of these same attributes, the results suggest that customers are most satisfied with *partner, product* and *core services*. *Value* and *communication* attributes represent the next level of satisfaction, with *supplemental services* having the lowest satisfaction. *Supplemental services* represents a statistically significant difference in satisfaction from the previously discussed attributes. As such, the improvement index suggests that *supplemental services* be prioritised for improvement opportunities.

After examining the results, the most important attributes have the highest satisfaction, suggesting that the sponsoring firm is appropriately devoting resources to those processes that are most important to customers. Even though *supplemental services* has lower than average importance, it possesses an importance score that is relatively close to those of other more important attributes. Yet, this attribute’s satisfaction is much lower relative to the other remaining attributes. While other improvement opportunities are possible, the data suggest that *supplemental services* be prioritised for improvement opportunities.

*Table 1*  Statistically inferred attribute importance scores

<table>
<thead>
<tr>
<th>Attribute composites</th>
<th>Statistically inferred importance scores</th>
<th>Customer satisfaction scores</th>
<th>Improvement index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partner</td>
<td>0.70</td>
<td>8.52</td>
<td>1.036</td>
</tr>
<tr>
<td>Product</td>
<td>0.67</td>
<td>8.51</td>
<td>0.998</td>
</tr>
<tr>
<td>Core services</td>
<td>0.66</td>
<td>8.67</td>
<td>0.878</td>
</tr>
<tr>
<td>Value</td>
<td>0.60</td>
<td>8.14</td>
<td>1.116</td>
</tr>
<tr>
<td>Supplemental services</td>
<td>0.56</td>
<td>7.76</td>
<td>1.254</td>
</tr>
<tr>
<td>Communication</td>
<td>0.53</td>
<td>8.20</td>
<td>0.954</td>
</tr>
</tbody>
</table>
**Maximum difference scaling and customer satisfaction analysis**

The researcher examined maximum difference scaling results to determine attribute importance for all customers, then identified three need-based segments using K-means cluster analysis. A customer satisfaction analysis was then conducted for each segment.

**Attribute importance**

The MaxDiff importance scores are very different from the statistically inferred importance scores. Table 2 contains the maximum difference scaling importance scores, along with statistically inferred importance scores.

The maximum difference scaling results display more variation than the statistically inferred importance scores, and tell a very different story of what is important to customers. Maximum difference scaling results suggest that *product* and *core services* contain 75% of the importance to customers, a very different interpretation compared to the statistically inferred importance scores. Whereas the statistically inferred analysis shows similar importance scores for *partner, product, service* and *value*, maximum difference scaling results demonstrate dramatic differences among these variables. The maximum difference scaling results demonstrate that *product* is nearly four times as important as *value* to the customer base. *Product* is nearly nine times as important to customers as compared to *supplemental services*, and four times as important to customers as compared to *partner*. These are significant differences.

While the rank order of attributes is similar between both methods, some discrepancies exist. For example, *partner* is the most important attribute in the statistical analysis, yet the fourth most important attribute in maximum difference scaling. Otherwise, the rank order is consistent

**Table 2** Comparing maximum difference scaling importance scores to statistically inferred importance scores

<table>
<thead>
<tr>
<th>Attribute composites</th>
<th>Maximum difference scaling importance scores</th>
<th>Statistically inferred importance scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>8.82</td>
<td>0.67</td>
</tr>
<tr>
<td>Core services</td>
<td>7.96</td>
<td>0.66</td>
</tr>
<tr>
<td>Value</td>
<td>2.19</td>
<td>0.60</td>
</tr>
<tr>
<td>Partner</td>
<td>2.07</td>
<td>0.70</td>
</tr>
<tr>
<td>Supplemental services</td>
<td>0.97</td>
<td>0.56</td>
</tr>
<tr>
<td>Communication</td>
<td>0.47</td>
<td>0.53</td>
</tr>
</tbody>
</table>
between the two methods, yet the differences in magnitude between the actual scores are significantly different.

- Answering research question 1: the MaxDiff importance scores are different from the current statistically inferred importance scores.

When examining customer satisfaction scores with maximum difference scaling importance scores (see Table 3), new priorities for improvement emerge. The improvement index suggests that product should be prioritised for improvement opportunities, followed by core services. While product and core services satisfaction scores are among the highest, their importance to the customer is considerable (75% of total importance for these two attributes). Given the importance of these two attributes, the improvement index suggests that product and core services are the two priorities for improvement opportunities. Using traditional methods, supplemental services were selected as a priority for improvement, yet this attribute is prioritised very low when using maximum difference scaling.

- Answering research question 2: using maximum difference scaling importance data as a key input of satisfaction analysis will result in different improvement priorities as compared to traditional methods.

**Table 3** Comparing maximum difference importance scores to statistically inferred importance scores

<table>
<thead>
<tr>
<th>Attribute composites</th>
<th>Importance scores</th>
<th>Customer satisfaction scores</th>
<th>Improvement index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>8.82</td>
<td>8.51</td>
<td>131.418</td>
</tr>
<tr>
<td>Core services</td>
<td>7.96</td>
<td>8.67</td>
<td>105.868</td>
</tr>
<tr>
<td>Value</td>
<td>2.19</td>
<td>8.14</td>
<td>40.734</td>
</tr>
<tr>
<td>Partner</td>
<td>2.07</td>
<td>8.52</td>
<td>30.636</td>
</tr>
<tr>
<td>Supplemental services</td>
<td>0.97</td>
<td>7.76</td>
<td>21.728</td>
</tr>
<tr>
<td>Communication</td>
<td>0.47</td>
<td>8.20</td>
<td>8.46</td>
</tr>
</tbody>
</table>

**Need-based segmentation, customer satisfaction and improvement opportunities**

A major advantage of implementing maximum difference scaling is the benefit of segmenting customers on importance scores (i.e. need-based segments). Previous segmentation efforts with stated importance scores were unsuccessful due to limited variation in the data.
Implementing K-means clustering analysis with maximum difference scaling data on the six attributes resulted in three need-based segments, which are included in Table 4. Clearly evident from the results, each of the need-based segments has widely varying importance values placed on different attributes. For example, the product-driven segment places over 67% of their importance on product-related attributes. In contrast, the service-driven segment places over 58% of their importance on core service-related attributes, and places much more importance on partnering as compared to the other segments. The value-driven segment places relatively equal levels of importance on product and service, with primary importance on value-related attributes.

**Table 4** Need-based segments from maximum difference scaling

<table>
<thead>
<tr>
<th>Product attributes</th>
<th>Product-driven segment</th>
<th>Service-driven segment</th>
<th>Value-driven segment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>14.3</td>
<td>4.2</td>
<td>4.6</td>
</tr>
<tr>
<td>Core services</td>
<td>3.7</td>
<td>13.4</td>
<td>4.0</td>
</tr>
<tr>
<td>Value</td>
<td>1.1</td>
<td>1.1</td>
<td>13.9</td>
</tr>
<tr>
<td>Partner</td>
<td>1.3</td>
<td>3.2</td>
<td>0.8</td>
</tr>
<tr>
<td>Supplemental services</td>
<td>0.4</td>
<td>0.6</td>
<td>0.2</td>
</tr>
<tr>
<td>Communication</td>
<td>0.4</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>Percentage of customer base</td>
<td>46%</td>
<td>44%</td>
<td>8%</td>
</tr>
</tbody>
</table>

The product-driven and service-driven segments contain the majority of customers (46% and 44%, respectively), with the smallest segment (8%) being the value-driven segment. Because these segments have different needs (importance of attributes), will these segments also have widely varying perceptions of satisfaction and possess different priorities for improvement?

**Customer satisfaction analysis for need-based segments**

The results of this section demonstrate that the attribute satisfaction scores are significantly different across the segments as well. Generally speaking, the service-driven segment is the most satisfied, and the value-driven segment is the least satisfied, with the differences being significant for all but one of the attributes (i.e. communication). Each of the segments will possess different improvement priorities, and all the improvement priorities are different from the traditional analysis conducted with statistically inferred importance analysis.
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Product-driven segment and improvement opportunities
After examining the results in Table 5, the improvement index suggests that product should be prioritised for improvement opportunities. Product is the most important attribute to customers, and satisfaction for this attribute is below core services and partner. If the firm wants to have the highest satisfaction with the most important attribute, then product should be prioritised for improvement opportunities with this segment.

Table 5 Customer satisfaction and improvement opportunities for the product-driven segment

<table>
<thead>
<tr>
<th>Attribute composites</th>
<th>Importance scores</th>
<th>Customer satisfaction scores</th>
<th>Improvement index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>14.3</td>
<td>8.35</td>
<td>235.95</td>
</tr>
<tr>
<td>Core services</td>
<td>3.7</td>
<td>8.64</td>
<td>50.32</td>
</tr>
<tr>
<td>Value</td>
<td>1.1</td>
<td>8.02</td>
<td>21.78</td>
</tr>
<tr>
<td>Partner</td>
<td>1.3</td>
<td>8.51</td>
<td>19.37</td>
</tr>
<tr>
<td>Supplemental services</td>
<td>0.4</td>
<td>8.13</td>
<td>7.48</td>
</tr>
<tr>
<td>Communication</td>
<td>0.4</td>
<td>8.21</td>
<td>7.16</td>
</tr>
</tbody>
</table>

Service-driven segment and improvement opportunities
Results from Table 6 suggest that the service-driven segment is the most satisfied. Across all attributes, this segment has significantly higher satisfaction scores compared to the other segments. Core services has the highest importance as well as the highest satisfaction. Likewise, product and partnering are the second and third most important attributes, and have second and third highest satisfaction, respectively. The sponsoring firm is optimising its performance with this segment by obtaining the highest satisfaction with the most important attributes. Examining the improvement index, core services is suggested for improvement opportunities. Core services is selected for further improvements because of its importance, even though it has the highest satisfaction. It is important

Table 6 Customer satisfaction and improvement opportunities for the service-driven segment

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Segment importance</th>
<th>Segment satisfaction</th>
<th>Improvement index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>4.2</td>
<td>8.82</td>
<td>4.96</td>
</tr>
<tr>
<td>Core services</td>
<td>13.4</td>
<td>8.92</td>
<td>14.47</td>
</tr>
<tr>
<td>Value</td>
<td>1.1</td>
<td>8.47</td>
<td>1.68</td>
</tr>
<tr>
<td>Partner</td>
<td>3.2</td>
<td>8.66</td>
<td>4.23</td>
</tr>
<tr>
<td>Supplemental services</td>
<td>0.6</td>
<td>7.55</td>
<td>1.47</td>
</tr>
<tr>
<td>Communication</td>
<td>0.4</td>
<td>8.29</td>
<td>0.68</td>
</tr>
</tbody>
</table>
to note that satisfaction is still below 9, the optimal threshold put forth by researchers (Reichheld 1993; Jones & Sasser 1995).

**Value-driven segment and improvement opportunities**

Examining the value-driven segment in Table 7 demonstrates a relatively dissatisfied segment, with attributes satisfaction scores being significantly lower than for the other segments. Looking across attributes, *value* and *supplemental services* have the lowest overall satisfaction scores. Clearly, perceptions of *value* need to be addressed with this segment, since *value* is the most important attribute and has a very low satisfaction score. Given the importance of *core services* and its relatively low satisfaction score, *core services* would also be prioritised for improvement opportunities with this segment.

**Table 7** Customer satisfaction and improvement opportunities for the value-driven segment

<table>
<thead>
<tr>
<th>Attribute composites</th>
<th>Importance scores</th>
<th>Customer satisfaction scores</th>
<th>Improvement index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
<td>4.6</td>
<td>8.02</td>
<td>9.11</td>
</tr>
<tr>
<td>Core services</td>
<td>4.0</td>
<td>7.63</td>
<td>9.48</td>
</tr>
<tr>
<td>Value</td>
<td>13.9</td>
<td>7.02</td>
<td>41.42</td>
</tr>
<tr>
<td>Partner</td>
<td>0.8</td>
<td>7.88</td>
<td>1.70</td>
</tr>
<tr>
<td>Supplemental services</td>
<td>0.2</td>
<td>6.78</td>
<td>0.64</td>
</tr>
<tr>
<td>Communication</td>
<td>0.2</td>
<td>7.72</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Consistent with the marketing literature, it is recommended that firms look at the relevant importance of each segment to the firm’s current and future success. Revenue, profitability and competitive intensity are just a few variables that may make a particular segment more or less attractive to the firm. Once need-based segments are identified, firms then need to recognise each segment’s current and potential value to the firm. Once segments are prioritised and targeted, the firm can decide on the improvement strategy (if any) for each segment.

**Comparing traditional methods to maximum difference scaling**

The most important conclusion is that implementing statistically inferred importance scores versus maximum difference scaling will result in different importance scores, which, in turn, will likely result in prioritising different attributes for improvement opportunities. For example, implementing maximum difference scaling, *product* is prioritised for improvement.
efforts, whereas implementing statistically inferred importance ratings suggests that supplemental services receive improvement efforts.

Consistent with previous research (Cohen 2003; Cohen & Orme 2004; Chrzan & Golovashkina 2006), maximum difference scaling results typically display much more variation and discriminating power. In this study, the general order and ranking of variables by importance was similar, yet differences exist. For example, partner was the most important attribute in the statistical analysis and fourth most important attribute in the maximum difference scaling analysis. While the rank order is similar, significant differences in the magnitude of importance scores were discovered for the attributes.

The significant increase in maximum difference scaling data variation allowed for meaningful need-based segmentation efforts. Three need-based segments emerged from the analysis, with each segment possessing significantly different needs (i.e. importance scores). In addition to identifying important need-based segments for strategic planning, these segments also have different prioritised improvement opportunities. Furthermore, there is a significant difference in satisfaction levels among the different need-based segments, suggesting that the firm is able to better meet the needs of different segments. For example, the value-driven is the smallest and the least satisfied segment. Management should prioritise these segments and make improvement efforts (if any) with the different segments in mind.

Conclusions

Maximum difference scaling is a valid research method to determine attribute importance for customer satisfaction research, which in turn can drive valid and meaningful need-based segments. Data from this paper suggest that researchers would deliver dramatically different improvement opportunities using maximum difference scaling versus more traditional methods.

This research project had several benefits for the sponsoring firm. First, the firm has much more confidence in the attribute importance ratings and the suggested improvement opportunities. Second, the firm now has a clear picture of different need-based segments in its customer base, along with the size and satisfaction of each segment. Given the complaining nature of the value-driven segment, management thought that this segment was much larger in size than the data suggest. This research has also helped management to better identify improvement efforts to more effectively
satisfy its targeted customers. As a result, satisfaction with targeted segments is now on the rise. The need-based segments are now also being used by management in acquiring new customers and migrating existing customers to the firm’s newer product platform.

The firm is investigating the use of maximum difference scaling as input to its quality function deployment efforts. Future research should examine the use of maximum difference scaling as a tool to gather importance data for quality function deployment. Finally, the firm is also investigating maximum difference scaling to understand attribute importance with its competitive benchmark surveys or industry-wide analysis. There are many research organisations that conduct industry-wide customer satisfaction analysis, and maximum difference scaling would be an excellent research method to implement for these surveys. Future research needs to examine the use of maximum difference scaling as a research methodology for gathering industry-wide customer satisfaction data.

References


**About the author**

Michael S. Garver is Professor of Marketing at Central Michigan University. He gained his PhD from the University of Tennessee. Dr Garver stays active within the business community through speaking, consulting, and conducting best practice research. His interests include using leading-edge methods for research in marketing and logistics. More specifically, Dr Garver has experience and expertise in conjoint analysis, maximum difference scaling, latent class analysis, data mining and structural equation modelling, and he is most known for his customer satisfaction, retention and segmentation research.

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