What’s Really Important?

It’s all in the eye of the beholder.

By Terry Grapentine and R. Kenneth Teas
How do researchers define the term “important”? Forty years ago, James H. Myers and Mark I. Alpert identified the crux of the problem when they observed that the term has two implied meanings—that which is desired and that which influences a purchase decision or product preference. (See Myers, James H. and Mark I. Alpert (1968), “Determinant Buying Attitudes: Meaning and Measurement,” *Journal of Marketing*, 32 (3), 13-20.) At that time, they noted the term “importance” was not well-defined in the literature and that it had become diluted by loose usage. “It usually connotes no more than a moderate relationship to decision-making, while we wish to discuss attitudes which are truly decisive [and] affect both the overall evaluation of an item and the actual purchasing decision,” said Myers and Alpert, who went on to coin the term “attribute determinance” in their 1968 *JM* article.

They later built on their previous work in the 1977 article “Semantic Confusion in Attitude Research: Salience vs. Importance vs. Determinance” (*Advances in Consumer Research*, 4, 106-109). Here they viewed the concept of importance as possessing three alternative meanings: (1) “salience” or top-of-mind recall of factors affecting a decision; (2) “importance,” the desirability of an attribute; and (3) “determinance,” the extent to which an attribute influences behavior or preference.

Salience was summarily dismissed as a valid indicator of determinance since top-of-mind recall can be affected by exogenous events such as exposure to advertising or a recently positive or negative experience with a product. Additionally, consumers may simply have trouble recalling all the “important” factors that affected their purchase decision. Finally, consumers may simply confuse what was “important” at the time of purchase vs. what factors would influence their next purchase decision.

Paul E. Green and Yoram Wind introduced yet a fourth conceptual view of importance by suggesting that importance is related to the utility consumers associate with different levels of attribute performance. (See Green, Paul E. and Yoram Wind, (1975), “New Way to Measure Consumers’ Judgments,” *Harvard Business Review*, July-August, 107-117.) As Green and Wind state:

“... in recent years researchers have developed a new measurement technique from fields of mathematical psychology and psychometrics that can aid the marketing manager in sorting out the relative importance of a product’s multidimensional attributes. This technique, called conjoint measurement, starts with the consumers’ overall or global judgments about a set of complex alternatives. It then performs the rather remarkable job of decomposing his or her original evaluation into separate and compatible utility scales by which the original global judgments or others involving new combinations of attributes can be reconstituted.”

With social scientists discerning the difficulty of defining the meaning of “important” as far back as the late 1960s, it perhaps is not surprising that attempts to measure the concept directly (e.g., “How important on a scale from 1 to 10 is ______?) would face considerable challenge in professional journals. Nevertheless, problematic direct measures of importance are unfortunately all too prevalent today in the applied marketing research setting.
**Executive Summary**

Measuring the concept of importance in marketing research is fraught with difficulties. Importance ratings are ambiguous because respondents ascribe different meanings to the term “important.” Compounding the problem, marketing managers often don’t clearly specify what they mean when they ask, “What’s important to our customers?” The conceptual definition of this term has inherent problems that researchers must address when measuring this concept and that marketing managers must address when discussing it.

**The Explanatory Power Problem**

The following graphic example depicts a typical way of asking a direct importance question. Assume this is a Web-based survey for purposes of discussion.

Example attribute importance rating on an Internet survey

Below is a list of attributes that may or may not have been important to you when you most recently purchased “X.” Use the scale provided by clicking on the number that best indicates how important each attribute was in your purchase.

<table>
<thead>
<tr>
<th>Not at all important</th>
<th>Extremely important</th>
</tr>
</thead>
<tbody>
<tr>
<td>○ ○ ○ ○ ○ ○ ○ ○</td>
<td>1 2 3 4 5 6 7</td>
</tr>
</tbody>
</table>

Scale length may change, and respondent directions may vary somewhat, but we place the crosshairs of our argument on the above example for the following reason: A considerable portion of the variance in the responses on the scale is the result of measurement error variance rather than the true differences across respondents.

If direct measures of importance provide valid information to the researcher, they should aid the researcher in developing models that explain consumer choice. Haemoon Oh reported the results of an empirical examination of this issue in the 1998 article “Evaluating the Role of Attribute Importance as a Multiplicative Weighting Variable in the Study of Hospitality Consumer Decision-Making” (Journal of Hospitality & Tourism Research, 21 (3), 61-80). Exhibit 1 illustrates his framework with hypothetical survey data and is described as follows:

- In addition to obtaining direct importance ratings, respondents rate the perceived performance of a product on the same attribute set.
- For each attribute, for each respondent, multiply the importance rating by the image rating. This produces a weighted attribute rating. For each respondent, sum these weighted ratings across all attributes. Separately, sum the unweighted image ratings.
- Across all respondents, separately correlate the sum of the weighted and unweighted attribute ratings with a dependent variable measure such as consumer satisfaction, perceived product quality, or future purchase intentions. Then compare the two correlations. (See Exhibit 2.)

Oh found that the unweighted index is a better predictor of satisfaction than the weighted measure. If the direct importance measures were contributing useful information, the explanatory power for the weighted index should have been higher than the unweighted model.

Even though the conceptual definition of “important” may change slightly from one study to another, there is other empirical evidence supporting the belief that the inclusion of importance ratings in consumer behavior models does not improve the explanatory power of the models. For example, Teas (1993) and Cronin and Taylor (1992) compared several weighted and unweighted models in terms of explanatory power. The results of both studies indicated that weighting attribute performance ratings by importance weights did not improve the explanatory power of the models.


**Potential Causes**

There are multiple problems associated with measuring the “importance” of an attribute directly, and these are (1) lack of variance in the measures; (2) concept vagueness; (3) attribute independence; (4) respondent knowledge; (5) attribute interaction effects; and (6) marketing manager effects.

Lack of variance in the measures. One possible reason for the explanatory power problem is that most attributes receive high scores. (See Wyner, Gordon A. and Hilary Owen (1993), “What Is Important?” Marketing Research, 5 (3), 48-50.) Generally, a majority of the attributes that end up on a survey are the ones that exploratory research suggests consumers’ desire. To the extent an importance scale primarily measures “desirability,” respondents tend to rate the items high, assuming that higher scale values denote greater “importance.”

Concept vagueness. Recent evidence suggests that one source of the problem associated with measuring attribute importance in consumer behavior research may involve the vagueness of the questions we ask respondents. When we ask an importance question containing vague terms, respondents often experience a need to clarify the question before they can provide an answer. An example of this type of issue is the “implied assumption” problem, which Gilbert A. Churchill and Dawn Iacobucci describe as “…a problem that occurs when a question is not framed to explicitly state the consequences; thus, it elicits different responses from individuals who assume different consequences.”

The resulting problem is that different respondents make different assumptions concerning the meaning of vague terms which, in turn, results in different assumptions concerning the
questions being asked. The result is that a portion of the variance in the data reflects measurement error rather than true opinion differences across respondents. For example, assume three identical respondents are asked to rate the importance of product quality when purchasing widgets. Their answers are as follows (higher numbers denote greater importance):

- Respondent A gives a rating of 7 because product quality is a desirable attribute.
- Respondent B gives a rating of 4 because product quality, although not the most important issue, did play a role in the last purchase decision.
- Respondent C gives a rating of 2 because, although the quality issue was very important in establishing the consideration set of products, the products in the consideration set are very similar in terms of product quality.

Because these three respondents are making different assumptions concerning the interpretation of the concept of “importance,” they are answering three different questions. The result produces measurement error variance in the data.

The issue of respondents’ use of question-clarifying assumptions when providing attribute ratings was examined by Teas (1993) in a study that explored respondents’ thought processes underlying their answers to a 7-point scale measuring consumer expectations. Teas found considerable evidence of measurement error variance resulting from respondents making varying assumptions about the meaning of the question being asked. For example, reasons respondents gave for not giving an attribute the highest rating of 7 on a 1-to-7-point scale were as follows:

- It is not feasible for a product to perform at a “7.”
- It is not likely that a product would perform at a “7.”
- The ideal amount of the attribute is less than “7.”

Clearly, these respondents were not answering the question the way it was intended to be answered. The first two reasons suggest the respondent did not rate the attribute a “7” because it was believed it was not possible to achieve a maximum amount with respect to the attribute. The third reason suggests the ideal level of the attribute is not a maximum amount. That is, an intermediate—neither too much nor too little—is the preferred level.

**Attribute independence.** A problem involving attribute independence occurs when different respondents make different assumptions about the degree of independence (a) across attributes or (b) from other exogenous factors. For example, consider the attribute “safe to operate” for a lawn mower. Two identical respondents might rate this “safe to operate” attribute very differently depending upon the assumptions they make concerning the extent the safety issue is being rated independently of cost considerations. One respondent who attaches high value to the safety issue might rate this attribute a 7 = extremely important, based on the following rationale: “I am giving this attribute a 7 rating because, holding everything else constant (e.g., price), safety is a very desirable product feature.”

However, a second respondent might attach a 5 = somewhat important rating to the same issue based on the following rationale: “I am giving this attribute a 5 rating because I know that all these extra safety features, although very desirable, will make the product more expensive. I’m willing to sacrifice a little safety in order to keep the price down.”

In actuality these two respondents may have very similar attitudes concerning lawn mower safety. However, because they make different assumptions about the independence between the safety and price attributes, they attach different importance ratings to the “safe to operate” product feature. Consequently, the survey data suggest that these two respondents have different attitudes when, in fact, they merely use different attribute independence assumptions when answering the question.

**Respondent knowledge.** An additional factor that Mark I. Alpert identified is that researchers who use measures of the importance of attributes sometimes incorrectly assume that respondents are aware of, and are willing to express, their true feelings. (See Alpert, Mark I. (1971), “Identification of Determinant Attributes: A Comparison of Methods,” *Journal of Marketing Research, 8* (2), 184-191.) As this argument goes, the decision process for many products is too complex psychologically for respondents to decompose it into its constituent elements (e.g., product attributes) and reliably state the relative impact of one attribute over another.

**Attribute interaction effects.** An additional problem associated with using direct measures of attribute importance relates to attribute interactions. For example, how important is the attribute “wide screen television”? For some consumers, the
answer depends on whether the television in question is a flat panel (easy to hang on a wall) versus a rear-projection television (impossible to hang on a wall).

Sometimes these interaction effects are more subtle. For example, how “important” is it for a young consumer to have an MP3 player on his cell phone? The importance of this attribute is a function of how much memory the phone has available to store songs—the greater the available memory, the greater the importance of the MP3 attribute.

Marketing manager effects. Another pernicious problem associated with the term “important” is that it clouds the thinking of marketing managers and blinds them to asking the right questions. Marketing managers often ask, “What’s important to our customers?” This is an ambiguous question. The manager may mean any one of the following:

• What does the customer desire?
• What will influence the customer’s decision?
• Is the customer willing to trade off X for Y?
• What is the customer willing to pay for various product features?

Unless marketing managers clarify the information they need, the marketing research results they receive will not be useful.

Potential Solutions
There is no perfect remedy to the problem of measuring attribute “importance” directly. Nonetheless, the first step that applied researchers need to take in finding a solution for their next project is to understand what the problems are. Clearly, academic researchers need to conduct more basic research in this area to discover whether these direct measures can be made useful for applied researchers. They also must determine under what conditions and assumptions we can have faith that they will produce somewhat valid data. With this in mind, we’ve developed the following potential solutions for the practitioner.

Eliminate direct measures altogether. One solution for the importance measurement problem is simply to eliminate the issue from the research project. In its place, one could use “preference regression” methods to derive the relative determinance (not “importance”) of attributes influencing some dependent variable measure, such as customer satisfaction or brand loyalty. Typically, preference regression works as follows:

• The dependent variable is some measure of preference, such as purchase intentions or brand loyalty.
• The independent variables are the product rating variables, typically grouped in “summated scales,” which measure more fundamental dimensions of a product.
• The partial regression coefficients serve as indices of determinance, reflecting the relative influence of the individual summated scales on the dependent variable.

This method does not allow for examining the determinance of individual attributes because of multicollinearity issues. For a detailed discussion of how this method can be used, see Terry Grapentine’s article, “Managing Multicollinearity,” in the Fall 1997 issue of Marketing Research.

Two methods available to researchers for improving the validity of attribute importance data ARE not “is” is to (a) replace direct rating methods with indirect decompositional methods and (b) attempt to improve the measurement validity of direct importance rating procedures by attacking the fundamental measurement validity problems.

Use decompositional measures. As suggested by Green and Wind many years ago, much progress has been made in improving the validity of importance measures via conjoint-type measures. Yet these tools also have their strengths and weaknesses. Regarding their strengths, conjoint methods do address several of the problems of measuring attribute “importance” directly. Consider the following:

• Concept vagueness. Conjoint-type measures require treatment levels to be defined unambiguously for respondents. For example, an attribute in a direct importance question might be “an engine powerful enough to meet my needs.” In a conjoint study, the researcher could specify precise engine sizes in terms of horsepower ratings for the respondent.
• Respondent knowledge. The conjoint task requires respondents to make choices from which the researcher can “decompose” the relative influence of different treatment levels on choice. This can remedy problems associated with some respondents having difficulty articulating how “important” an attribute was or is in a purchase decision.
• Attribute interaction effects. Conjoint methods allow for modeling attribute interactions explicitly, whereas this is problematic for direct attribute importance measures.

Some weaknesses of decompositional methods are (a) limits on the number of treatments and treatment levels (although some recent advances have been made in this area); (b) the task itself is hypothetical—actual decision making is not being measured; and (c) sometimes the number of treatment levels and the range of those levels can bias respondent evaluations of the stimuli. Several articles on this topic have appeared in previous issues of Marketing Research. For more information, see Paul E. Green and Abba M. Krieger’s article

A portion of the variance in the data reflects measurement error rather than true opinion differences across respondents.
“What’s Right with Conjoint Analysis?” in the Spring 2002 issue of Marketing Research.

Direct Measures to Consider

Several alternatives are available to the applied researcher for measuring attribute importance. Two examples, which have some support in the literature, include the constant sum measure and the information display board.

**Constant sum measure.** Several authors have found that a constant sum scale produces results similar to conjoint analysis with respect to the rank order of attribute determination. For more information, see Teas, R. Kenneth and Terry Grapentine (2004), “Testing Market Positioning Themes: A Perceptual Mapping Approach,” Journal of Marketing Communications, 10 (4), 267-288.

**Information display board.** Roger M. Heeler, Chike Okechuku and Stan Reid found significant measurement validity in an information display board (IDB) in which subjects selected information pieces from an attribute-by-brand matrix board until they acquired enough information to make a product selection. (See Heeler, Roger M., Chike Okechuku, and Stan Reid (1979), “Attribute Importance: Contrasting Measurements,” Journal of Marketing Research, 16 (1), 60-63.) They argued that the “…complete information acquisition behavior of the subject can be followed through the IDB,” and the relative determinance of the attributes inferred from the “decision process.”

**Testing Direct Measures**

Regardless of the direct measurement approach used, an excellent way to examine how well an “importance” scale is performing is to conduct a depth interview of a small sample of respondents.

The interview focuses on why respondents answered the direct scaling questions the way they did. Two questions that can be used are “Why did you check 5 on question No. 2?” or “Why didn’t you give this attribute the highest rating?” The respondent is encouraged to reconstruct the thought process used when answering the question. For a detailed discussion of this procedure, see Teas (1993).

If different respondents are constructing different assumptions when responding to the importance scales, the assumptions will generally be revealed using these procedures. The primary way to eliminate the assumption problem is to make the assumptions explicit. For example, in a previous example, a hypothetical respondent who was rating the “importance” of safety in purchasing a lawn mower did not give the highest rating to a highly safe lawn mower because it “would cost too much.” This problem can be avoided by instructing respondents to assume the performance of a lawn mower on a given attribute is not affected by the lawn mower’s price. Or respondents can be instructed to focus on the most recent purchase, the next purchase, or the role various attributes would play in a decision after the respondent has narrowed his choice down to a few brands. The key is to have all the respondents making the same assumptions when answering the question, thereby eliminating error variance.

“What’s important to our customers?” is a complex question that has a simple, easy to understand, wrong answer. Measuring the concept of importance in marketing research is problematic because the term is ambiguous, and the nature of the importance construct is, by its very nature, difficult to define operationally. This article illustrates the challenges confronting applied marketing researchers in measuring “importance” and offers several ideas and suggestions to consider when doing so.

Indeed, the use of direct measures to gauge the influence that attributes have on the decision process is daunting. We realize that many companies will continue to use direct measures of “importance” out of convenience and the need to do quick and relatively inexpensive research. We hope this discussion gives researchers pause before immediately relying on these direct measures. Unfortunately, we have found that attempting to make implied assumptions explicit in questionnaires sometimes leads to rather lengthy questionnaire instructions. After the third or fourth attribute, respondents forget the instructions and relapse into making assumptions about the nature of the remaining attributes and their independence from each other.

More generally, this article reflects the inherit difficulty of measuring the attitudes and beliefs underlying the consumer decision process. As researchers, we need to be ever mindful of how well our survey instruments measure what we think they are measuring. ●

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