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# PROBLEMS WITH DERIVED IMPORTANCE MEASURES IN BRAND STRATEGY AND CUSTOMER SATISFACTION STUDIES

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## INTRODUCTION

For over half a century, marketers have studied the determinants of brand choice for products and services. The most common approach for addressing this issue has been to ask respondents to “self-report” the importance of, typically, 10-50 different product/service attributes and benefits in a product category. For example, in assessing which characteristics drive overall preference for a retail business (say, a local supermarket or neighborhood bank), researchers ask a question such as: “On a scale of 1-5 how important to you is “an extremely clean store?” The answer categories are: “extremely important” = 5, “very important” = 4, “somewhat important” = 3, “slightly important” = 2, and “not important at all” = 1. This question, of course, could be asked with any number of self-reported importance measures, including 7-point scales, each point verbally anchored, or a 10-point, 1-10, or 11-point, 0-10, with or without verbal anchors. The pairwise correlation between any two of these measures is virtually always .9 or greater – in other words, the different measures are interchangeable. Self-reported importance is self-reported importance.

By the 1970s, however, it became evident that in many cases what respondents said was important was not reflected in their brand choices. Rational, tangible, “price of entry” characteristics tended to be rated high, while intangible, emotional, some would say “irrational” attributes and benefits, tended to be rated low. Yet, practitioners found that there are many product categories where intangible traits are of critical import (e.g., automobiles, beer, clothing, cosmetics, soft drinks, vodka and scotch), despite the fact that people tend to rate them low, and other product categories where the rational traits are often characteristics that every brand has to have (“prices of entry”), but don’t differentiate between brands, and therefore don’t drive brand choice. To help overcome this weakness in the assessment process, during the

1980's and 1990's to date, an *indirect* measurement approach became a popular way to assess the influence of attributes and benefits on brand choice or customer satisfaction. This is accomplished by rating a brand, better yet, all the leading brands in a category, in terms of the 10-50 attributes and benefits mentioned earlier and then correlate (using a variety of tools we'll note later) these perception ratings with overall preference, buying behavior or satisfaction and loyalty. This analysis might lead, for example, to a statement such as: we found that "clean stores" has the closest relationship with buying preference for, or overall satisfaction with, Kroger's or supermarket chains in general.

This indirect approach to assessing the relative import of different attributes and benefits is called "derived importance," the word "derived," indeed indicating the indirect approach taken. Today, every leading research firm employs the "derived importance" method using different statistical tools to measure this phenomenon (i.e., the relationship between the degree to which a brand is perceived to have an attribute, and purchase intent for that brand). Among the most prominent are 1) cross-sectional "correlation" analysis, relating specific attributes and overall brand choice (or overall satisfaction); 2) correlation analysis between *changes* over time on specific attributes, and *changes* over time in brand choice or overall satisfaction, and 3) structural equation modeling, a sophisticated form of #1 above. By far, the most frequently used of these methods is #1 - the cross-sectional correlation method – an analysis based on data collected at a single point in time. This popularity is due partly to the simplicity of the technique, partly due to the technique's space-saving-on-a-questionnaire aspect, and partly due to the added expense of #2 above (i.e., examining respondents at more than one point in time), and the lack of knowledge and experience to interpret and implement #3.

Basically, using this cross-sectional correlation method in the brand choice context, many different attributes/benefits are rated by consumers (or industrial buyers) with respect to

the degree to which a brand is perceived to have the attribute (e.g., tastes “minty,” “freshens breath,” etc., for a tooth paste; other attributes for a luxury automobile). A high correlation for a given attribute is then said to indicate that the aforementioned attribute is a major driver of brand choice for that product category. In a “driver of overall satisfaction” context, the correlation is between the satisfaction with the degree of the attribute the service provides and an overall satisfaction or loyalty measure. Both forms of derived importance measurement – to predict brand choice and to predict customer satisfaction – are often called “leverage analysis.”

The first published example of the technique was reported by Alvin Achenbaum in a seminal paper titled, “Knowledge is a Thing Called Measurement” (Achenbaum, 1966). Forty years later it’s a very common tool employed by practitioners all over the world, despite any evidence of its predictive validity. That is to say, there is no evidence that a new positioning strategy, product strategy, or loyalty enhancement strategy based on the results of a derived importance analysis yields a more favorable outcome than a strategy based on methods such as concept testing, which do not rely on correlation analysis, or judgment alone.

A Google search in July, 2008 revealed over 700,000 citations identifying articles, blogs, etc., under “derived importance in marketing research,” many of them dealing with how the methodology has been employed to draw inferences about the predictors of brand choice and customer satisfaction. A few examples are, “Analytics in Competitive Intelligence: Stated Importance vs. Derived Importance” (Dalley, 2007), “Comparing Derived Importance Weights Across Attributes,” (Wittink, Krishnamurthi and Nutter, 1982) and “Derived Importance-Performance Analysis: a Diagnostic Tool for "Main Street" Planners” (Wiles, 2002).

It is also the method outlined by the Business Research Lab (2003) noted at *employeesurveys.com*, when describing their technique for “deriving attribute importance with correlation analysis.” Indeed, The Business Research Lab specifically refers to the technique as

“leverage analysis” in its website. Its use in the medical survey arena is illustrated in the website of *MedicalSurveys.net*, in an article entitled, “Measuring What Is Important to Patients” (Combs, 2002). The technique’s acknowledgment in indicating drivers of customer service is described in “The Keys to Key-Driver Analysis” (Hochster, 2001), where attribute ratings are correlated with likelihood to purchase. Init-Satisfaction (2003) describes how “a given characteristic will be judged important if the overall level of satisfaction is sensitive to the variation of the satisfaction with this characteristic,” going on to essentially describe a correlation analysis as has been detailed above. Chynoweth describes the same technique in his discussion of “variance markers” in survey design (Chynoweth, 2003), indicating how a given attribute will be judged important if the characteristic is highly related to overall satisfaction.

Whether the specific technique used to find the derived importance literally uses product-moment correlation coefficients or other proportional-reduction-in-error measures that, essentially, yield similar results (e.g., Beta Coefficients, Jaccard Coefficients, Kano Coefficients or Path Coefficients), these “statistics” have serious problems which we will now discuss.

#### DERIVED IMPORTANCE COEFFICIENTS MAY YIELD MISLEADING INFORMATION: A SINGLE PHOTOGRAPH IS NOT A MOTION PICTURE

The first major problem is that most derived importance analyses undertaken today are cross-sectional in nature. This is curious since most such studies assume that changes in perceptions on one or more attributes will lead to changes in brand preference or loyalty. In other words, causal implications are being drawn from point-in-time data, not longitudinal data. One simple example worth noting is that at a fixed point in time, the correlation in most product categories between a brand’s share of advertising spending and a brand’s share of market, averages around .93 (Clancy, 2003; Clancy & Shulman 1990). This is not surprising, because in

many product categories, particularly packaged goods, the advertising budgets are set as a fairly standard percent of sales. If, indeed, that is the case for all the “players” in the category, the high correlation is tautological. However, the correlation between *changes* in a brand’s share of advertising spending and *changes* in a brand’s share of market drops to less than .1 (Clancy, 2003; Clancy & Shulman, 1990). A more recent work by the Marketing Science Institute reveals that the elasticity coefficient for changes in advertising expenditures with changes in market share is a paltry .01 (Clancy & Krieg, 2007). In other words, longitudinal analyses suggest that advertising alone has very little effect on sales—which we regard as the “true” effect—while the cross-sectional analysis would lead to the misleading conclusion that it is a prime determinant of sales.

Interestingly, while Achenbaum, in 1966, discussed “changes” in brand perception, and changes in share of users, in fact, he used cross-sectional data and inferred causation through a point-in-time regression analysis. This overwhelming use of cross-sectional analyses which, as we will argue, rarely leads to correct conclusions, may explain in part why the average ROI of advertising expenditures in both B2B and B2C categories appears to be negative (Clancy and Stone, 2005). Stated differently, if many advertising strategies are based on a tool which leads to the wrong conclusion about a positioning or message strategy, then it should be no surprise when the strategies fail.

It may come as a shock to many practitioners that there is no predictable relationship between cross sectional correlation(s) and “longitudinal correlation.” Suppose that  $Y$  = Brand Share, and  $X$  = Advertising Expense, and we have  $n = 10$  brands in our study. Suppose further that we have data on  $Y$  and  $X$  at two points in time,  $T_1$  and (later)  $T_2$ . Thus, we have 20 sets of  $(Y, X)$  values:  $(Y_1, X_1)$  at  $T_1$  for each of 10 brands and  $(Y_2, X_2)$  at  $T_2$  for these same 10 brands. Define  $R_1(Y, X)$  as the correlation between  $Y_1$  and  $X_1$  (i.e., across brands at time 1), and  $R_2(Y,$

X) similarly (across brands at time 2). Also, define for each of the 10 brands,  $\Delta Y = Y_2 - Y_1$ , and  $\Delta X = X_2 - X_1$ , and  $R(\Delta Y, \Delta X)$  as the correlation between  $\Delta Y$  and  $\Delta X$  across brands. Of course,  $R_1(Y, X)$  and  $R_2(Y, X)$  are the respective cross sectional correlations, while  $R(\Delta Y, \Delta X)$  is the longitudinal correlation. Consider the following examples: In Table 1, the data yield the following –

Table 1  
Data with High Cross-Sectional Correlations  
AND  
High Longitudinal Correlation

<u>Y1</u>	<u>X1</u>	<u>Y2</u>	<u>X2</u>	<u>ΔY</u>	<u>ΔX</u>
10	12	20	31	-10	-19
13	16	10	18	3	-2
7	10	5	11	2	-1
9	11	4	8	5	3
15	18	30	45	-15	-27
7	8	10	18	-3	-10
12	15	7	13	5	2
16	18	9	16	7	2
11	14	11	18	0	-4
13	15	18	18	-5	-3

$$R_1(Y,X) = .980$$

$$R_2(Y,X) = .954$$

$$R(\Delta Y, \Delta X) = .950$$

All of these results are high, and each significant at  $p < .0001$ . The data in Table 2 yield the following results on the following page:

Table 2

Data with High Cross-Sectional Correlations  
AND  
Low Longitudinal Correlation

<u>Y1</u>	<u>X1</u>	<u>Y2</u>	<u>X2</u>	<u>ΔY</u>	<u>ΔX</u>
10	12	1	11	9	1
8	11	3	30	5	-19
7	9	2	19	5	-10
10	14	5	48	5	-34
7	10	3	32	4	-22
14	15	6	58	8	-43
13	13	5	52	8	-39
15	17	3	29	12	-12
14	18	6	56	8	-38
14	17	4	43	10	-26

$$R_1(Y,X) = .920$$

$$R_2(Y,X) = .992$$

$$R(\Delta Y, \Delta X) = .097$$

Here,  $R_1(Y,X)$  and  $R_2(Y,X)$  are similarly high (with each  $p < .0001$ ), *but*  $R(\Delta Y, \Delta X)$  is quite low, and not significant, with  $p > .75!$

This example clearly illustrates how the  $R_1$  and  $R_2$  values can be about the same (both are in the 90's for each table of data), while having VERY different values for  $R(\Delta Y, \Delta X)$ . In turn, this indicates how the  $R(\Delta Y, \Delta X)$  cannot be inferred from the  $R_1(Y,X)$  and  $R_2(Y,X)$  values.

Since virtually all “derived importance” studies undertaken today are cross-sectional in nature, and because, as we have demonstrated, cross-sectional correlation is not the appropriate approach for addressing this issue, “derived importance” analysis is a highly suspect methodology.

However, even if this problem magically went away and cross sectional correlation yielded correct outcomes, there are still serious issues to be considered. In an earlier paper we showed that aggregate level correlation analysis—the most widely employed methodology today—produces coefficients which are different in magnitude and sometimes direction than coefficients based on individual respondent level data (Clancy, Berger and Magliozzi, 2003). Because we are trying to infer the rank order importance of attributes for individual respondents—and then aggregating them to a sub-group or total sample—the proper analysis is at the individual respondent level. This is almost never done by commercial research firms and the marketers who employ them.

#### WHAT DO THESE CORRELATIONS COEFFICIENTS REALLY MEAN?

We have used the words, “correlation” and “cross-sectional correlation” numerous times. However, just what are we correlating over what? There are, in a sense, four dimensions to the data set – brands, attributes, respondents, and the two measures for each combination (the degree to which a brand is perceived to have the attribute, and a dependent variable such as purchase intent for that brand or brand choice – or analogous measures for the satisfaction setting). Apparently, the word, “correlation” is often taken for granted. In practice, this supposedly simple correlation analysis is conducted four different ways – *only one of which is sensible upon deeper analysis* (Clancy, Berger, and Magliozzi, 2003).

Yet, even if the correct method of performing the correlation analysis is utilized, the traditionally-suggested conclusions from the results may not be correct. The root of this failing is the simple fact, taught in every elementary statistics class, *that correlation does not necessarily imply causation!!*

As noted, there is a “standard” interpretation of the correlation analysis discussed above. If the correlation is “highly positive,” that attribute is viewed as an important driver of brand choice, and consumers prefer more of the attribute to less of the attribute. In the context of predicting overall satisfaction, the interpretation is similar – this component of service/satisfaction is a driver of overall satisfaction, and, of course, the more satisfied with this component the better. If the correlation is “highly negative,” that attribute is viewed (also) as an important driver of brand choice, but consumers prefer *less* of the attribute to more of the attribute. Finally, if the correlation is near zero (perhaps, “not significant”), conventional analysis suggests that the attribute is relatively unimportant to brand choice, or in the satisfaction setting, unrelated to overall satisfaction.

However, we now present eight examples that illustrate how the above “taxonomy” of interpretations of the derived importance using correlation analysis is problematic. There exist analogous illustrations for the other methods alluded to earlier for determining derived importance (ultimately, by whatever method, quantifying the relationship between the degree to which a brand contains an attribute and brand choice, or the relationship between satisfaction on a particular dimension of service and a measure of overall satisfaction or loyalty).

## BEWARE UNDERESTIMATING THE INFLUENCE OF NEW IDEAS AND INNOVATIONS

Consider an attribute that is innovative and a breakthrough, and that no brand currently delivers. This could be fingerprint ID’s at an ATM (no more having to carry a card around, no chance of a stolen card, etc.), a combustion engine that doubles mileage without added cost or any other change in performance, special anti-oxidants in a soft drink without any compromise in taste.

All “brands” of banks, or oil companies, or soft drinks, will achieve low scores on such a dimension because none of them have it while brand choices will be whatever they are. The correlation will be zero, or very near zero, regardless of the respondents’ brand preferences. Thus, the routine interpretation will be that the attribute has no importance to brand choice. Yet, if the attribute is highly appealing (as the ones mentioned above may be), and the “brand” (bank, oil company, soft-drink company) offered the attribute, the company would benefit greatly – it would be a successful new product or service. Indeed, the attribute would drive brand choice! The implication here is that derived importance analysis in this situation can be misleading, and would have to be supplemented by either self-reported importance or desirability ratings or new-concept purchase probability ratings in order to be certain that the appeal of new ideas and innovations is properly understood.

#### UNFAMILIARITY IS A RELATED PROBLEM

Consider an attribute that may have been around for years and, therefore, is not really new or innovative, yet, many people have not heard of it before. Consider Mammotome, a breakthrough breast biopsy technology. Though available in many hospitals, large segments of the population have never heard of it. Take, as another example, “Taurine,” the magic ingredient in Red Bull, which has been one of the fastest growing soft drink brands for years. These Unfamiliarity cases are similar to the Innovation example in their arithmetic. *All* brands receive a low score within some sub-groups in the population (i.e., people who never heard of the attribute, and, therefore, rate it low on importance.) As a result, the correlation is, again, near zero. The traditional implication, again, is that the attribute is unimportant. Yet, the attribute is potentially very important – although possibly requiring the education of the public about its benefits - and the brand offering the attribute would potentially profit significantly. While being

similar to the Innovation example in its arithmetic, the essence of the situation differs from the Innovation setting.

#### REVERSE CAUSALITY LEADS IN THE WRONG DIRECTION

Now consider an attribute that is associated with market leadership because customers believe that the “best” companies “of course” offer it. This could be the offering of extensive insurance coverage (for a bank), a website that lists TV shows in which it advertises (for, say, an oil company), a global hotline for advice on ingredients and recipes (for, say, a food products company).

All big banks, or well-known oil companies, or highly popular food brands will achieve a high score on these attributes (since they will be *assumed* to have them, due to their market leadership), while small banks, and less-familiar, smaller oil and food brands receive low scores on each of these attributes (since they will be *assumed* not to have it, or, at minimum, survey respondents won’t be sure whether or not they have it). Of course, *by definition*, brand preferences will be higher for the larger brands (commensurate, indeed, with being a larger brand!). Thus, the correlation will be highly positive. Accordingly, the routine and incorrect interpretation will be that the attribute is of high importance to brand choice.

But, if the companies having the attribute took it away, few people would care. (How many customers choose a bank because of its insurance offerings, or who choose an engine lubricant due to its website, or a food brand due to its global hotline? We can’t imagine a working mother with three small children choosing her soft-drink brand based on the presumed existence of a global hotline). The monies “invested” in these attributes could *surely* be spent on something else with a superior marketing investment return.

In the “Innovation” case, one *might* argue that “somebody” would catch on to the fact that the result appears misleading. However, we would argue that in this “Reverse Causality” case, there is no clear indication that there is an issue, and, while somebody might be surprised at the result, there would be no obvious reason to doubt the result unless specifically seeking out misleading results.

#### “PRICE OF ENTRY” RELATIONSHIPS ARE OFTEN MISINTERPRETED

Next consider an attribute that everyone wants, and every brand currently delivers. This could be accurate monthly statements (for a bank), a choice of gasoline grade at the self-service pumps at a gas station (for an oil company), or appropriate carbonation (for a soft drink brand).

All brands achieve a high score on the amount of the attribute each has (since all brands indeed have it). Thus, regardless of brand preferences, the correlation will be nearly zero. Accordingly, the routine interpretation will be that the attribute is of no importance to brand choice.

Obviously, if you took the attribute away, the company (bank, oil company, soft drink company) would suffer grievously, while if you promoted the attribute more, the brand would, in all probability, not perform any better.

#### USE CAUTION WHEN ASSESSING INTANGIBLE, IMAGE ORIENTED TRAITS

Consider an attribute for which many customers have difficulty addressing the degree to which a brand has this attribute, because of the attribute’s intangibility. An example, which can apply to many different companies and services, would be “(the brand) makes me feel successful.” Another example might be “youthfulness” in a soft drink context. One major reason for the difficulty in rating brands on intangible, image-oriented dimensions (i.e., “attributes”) is,

in part, because it seems irrational to apply animate descriptions to inanimate objects. Some respondents perceive the exercise as “silly” and fail to provide a thoughtful response.

As a consequence, many scores assigned to the brands will be randomly distributed across brands (and will likely all be relatively low – although this is not critical to the example), and the correlation will be weak (i.e., near zero).

But beware: practitioners have discovered over the past three decades that if such a dimension is highly appealing (and, such intangible dimensions as “successful” or “youthful” *can* be highly appealing), a brand might well benefit from a positioning that promises this dimension. This problem is better addressed by the “motivating power” approach which has been discussed elsewhere (e.g., Clancy and Krieg, 2000; Clancy and Krieg, 2007) or through positioning testing and/or copy testing.

#### SPURIOUS CORRELATIONS YIELD SPURIOUS RESULTS

Consider an attribute that is not important, but one or more large brands have it and smaller brands do not have it. An example would be patriotic red and blue packaging for a soft drink, golden arches for a fast food restaurant and global financial assistance for a bank. In these cases one or more large brands (i.e., Pepsi, MacDonald’s and Bank of America respectively) get high scores, and small brands (e.g., Fanta and A&W and community banks) get low scores. Even if only one large brand has the attribute and all other brands do not, the correlation will be relatively high and the implication is that the attribute is important. Yet, if you strengthened the large brand(s) on this attribute, nothing would happen. On the other hand, if you strengthened the small brands on this attribute, you would create perceptual confusion at point-of-sale (and, of course, in some cases, legal issues would arise) and improved sales are not likely to occur.

This example is similar to the Reverse Causality in its arithmetic, but again the setting is different. In the former case, the attribute is inferred to belong to the larger brands (likely due to market leadership), while here, the attribute is actually present in one or more of the large brands.

#### WHEN DIFFERENT SEGMENTS OF THE MARKET ARE LOOKING FOR DIFFERENT THINGS

Market segmentation should play a clear role in the interpretation of derived importance data but, in our experience, rarely does. Consider an attribute that many consumers “love” (or, perhaps, “strongly desire”), while other buyers “hate” the characteristic (or find it “strongly undesirable”). Examples would be genetically-altered vegetables (so called “Frankenstein foods”) which are resistant to insects and therefore are grown without pesticides, or very fast acceleration in an automobile (0-60 acceleration in under 6 seconds). Brands that have the attribute would earn a very high purchase-intent score among segments of the population desiring this attribute, and a low purchase-intent score among segments of the population who find it unappealing. The correlation could be near zero. The closer to 50/50 the consumers are split on their enthusiasm for and against the attribute, the closer to zero the correlation. Therefore, the mechanical result generated would be that the attribute is unimportant when the attribute might be of critical importance, and its criticality totally unrecognized. One approach that some researchers have taken to avoid this problem is to employ symmetric desirability scales as opposed to an asymmetric importance scale or any derived importance measure (e.g., Clancy and Shulman, 1990).

## CAUTION: THERE MAY BE INTERACTIONS BETWEEN ATTRIBUTES

Consider (for the first time) TWO attributes simultaneously. Call them X and Y. Suppose that the two attributes are somewhat redundant in their importance to a consumer. An example might be X = donating a portion of profits to environmental causes, Y = donating to the coffers of very liberal democratic candidates. We envision that the importance to a consumer of a brand having X and the importance of a brand having Y are highly positively correlated. And, for the purity of this discussion, let us ignore the potential for the “half and half” issue of the previous section, and assume that X and Y are important and desirable to the majority of consumers (or, equivalently, important and desirable to the specific target market).

Then, when evaluating the degree to which brands have attribute X, the brands having it get high scores, and the brands without it get low scores. The correlation is highly positive and the attribute is rightfully judged to be important. The exact same scenario holds for attribute Y. However, it may well be the case that if the brand possessed *only* X, or *only* Y, the brand would be just about equally well-off (i.e., it is no better off possessing both attributes!). This would never get revealed by the use (virtually always in practice) of “univariate” analysis (i.e., one attribute at a time), although it would likely get revealed through the use of factor analysis as a preliminary step before doing the derived importance computations. Unfortunately, oftentimes this preliminary step is not taken because practitioners have tight deadlines and budgets which constrain how much analysis can be done.

The situation could be even worse for the brand if, instead of X and Y being highly positively correlated, X and Y are highly *negatively* correlated. An example might consist of a charity that (X) promotes the fact that it is very frugal with expenses (surely, by itself, a virtue that, everything else equal, could lead to higher contribution levels), and also (Y) sends out relatively expensive promotional pieces, with luxurious acknowledgments of pledges, etc.

(again, by itself, likely leading to higher contributions levels). Having both of these “attributes” could easily lead to a charge of inconsistency or disingenuousness, and lower contribution levels. The charity would be better off having only X or only Y, but instead of equally well-off as having both X and Y, it might now be *worse* off having both X and Y.

Our example is based on an assumption of redundancy between two attributes. Statistical interaction, of course, does not require the attributes to be correlated at all. Consider low calories and high sodium in a soft drink, or high fees and unfriendly service in a bank. Either one of them could turn prospects away and customers off, but the additive effects of having both characteristics might understate the true negative effect of the combination. Thus, possible interactions, like everything else we have been discussing, can be a source of faulty decision-making in a derived importance application.

## SUMMARY

First, we noted that, based on current marketing research literature and practice, using cross-sectional correlation analysis to determine derived importance scores is prevalent in marketing research practice today. All the commercial research firms employ this tool and marketers use the results to make strategy decisions. We next noted and referenced how this simple-seeming method needs to be examined carefully to ensure that the “right” correlation analysis is chosen. We generally favor correlations based on changes in perceptions and changes in preference or loyalty, calculated at the individual respondent level. Then, we presented eight practical examples of situations when the routine application of derived importance analysis is misleading, and will result in strategies that contribute to negative ROI.

Some of the examples (e.g., Innovative attributes, Unfamiliar attributes, Price-of-Entry attributes) illustrated how the correlation could be near zero, but the attribute very important.

Other examples (e.g., Reverse Causality) illustrated how the correlation could be near 1.0, but the attribute unimportant. Even among the first set of examples, which exemplify how the correlation can be near zero, yet the attribute very important, there are differences in “the path” to this condition. In the Innovation and Unfamiliar examples, the low correlation is driven by the fact that all brands received a LOW score for having the attribute, while in the Price-of-Entry example, the low correlation is driven by the fact that all brands receive a HIGH score for having the attribute. For Intangible/Image-Oriented traits, another case where the correlation is near zero, but the attribute important, the driver of the near zero correlation is not that the brands all get the SAME rating, but that the ratings are random, not related to anything identifiable. Several other cases are, in some sense, more subtle – as illustrations, the market-segmentation-based half and half example and the interaction example.

There are many solutions to these problems which are beyond the scope of this paper. Factor analysis is always useful because it tests for redundancy in items, and often leads to a greater understanding of what the items mean and how they are linked to more fundamental constructs. The symmetric desirability scale we referred to earlier has some powerful benefits. It provides an ability to measure the positive or negative valence of a particular attribute or benefit. Some people can tell us, for example, that a 0-60 acceleration in under 6-seconds is desirable while other, more cautious drivers might tell us that it’s highly undesirable. This is an outcome not picked up by either the traditional self-reported importance approach or the derived importance discussed in this paper. “Problem Detection Analysis,” a method which appears to be fading into obscurity in the marketing research profession, is an alternative approach to desirability, importance and derived-importance measures, and provides deep insight into what the problems are which, if solved, would drive future behavior in any product category (Clancy and Krieg, 2007). Still another approach which overcomes the challenges of derived importance

is the *motivating power* methodology which has been employed by a few different firms in different forms since the early nineties (Clancy & Krieg, 2000, 2007).

Our overall recommendation is to be wary of traditional point-in-time correlation-based derived importance scores. As simple and inexpensive as these data are to collect and analyze, the results can be dangerously misleading. Derived correlation can lead to a contrived disaster and a company deprived of revenues and profits.

## REFERENCES

- Achenbaum, Alvin (1966) "Knowledge is a Thing Called Measurement," *Attitude Research at Sea, AMA Monograph*, edited by Lee Adler and Irving Crespi.
- Center for Survey Research (2001) "Summary of Results: 2001 VDOT Customer Satisfaction Survey," *Report of the Center for Survey Research*, University of Virginia.
- Chynoweth, George H (2003) "Variance Markers in survey Design," <http://www.isixsigma.com/library/content/c030922a.asp>.
- Clancy, Kevin (2003) "Methodological Problems in Studies of Customer Satisfaction," presented at the *American Marketing Association Frontiers in Marketing* conference, Bethesda, MD, October.
- Clancy, Kevin J, Paul D. Berger, and Thomas Magliozzi (2003). "Illustrations of the Ecological Fallacy in Advertising Research," *Journal of Advertising Research*, December, p.370-380.
- Clancy, Kevin J, Peter Krieg, (2000) "Counterintuitive Marketing: Achieve Great Results Using Uncommon Sense," New York: The Free Press – A Division of Simon and Schuster.
- Clancy, Kevin J, Peter Krieg, (2007) "Your Gut is Still Not Smarter Than Your Head: How Fact-Based Marketing Can Drive Growth and Profits," Hoboken, New Jersey, John Wiley & Sons.
- Clancy, Kevin J, Randy Stone (2005) "Don't Blame the Metrics" *The Harvard Business Review*, Vol. 83, No. 6, June, p. 26-28
- Clancy, Kevin J, Robert S. Shulman (1991) "The Marketing Revolution: A Radical Manifesto for Dominating the Marketplace" New York: HarperBusiness - A Division of Harper Collins Publishing.

Combs, Melanie (2002) "Improving Service From the Customer's Perspective: Medicare's Program Integrity Experience," [http://www.medicalsurveys/tips/patient\\_satisfaction](http://www.medicalsurveys/tips/patient_satisfaction).

Dalley, Christopher, (2007), "Analytics in Competitive Intelligence: Stated Importance vs. Derived Importance," *Intelligence for Business*,  
<http://primaryintelligence.blogspot.com/2007/06/analytics-in-competitive-intelligence.html>.

Hochster, Michael (2001) "The Keys to Key-Driver Analysis," *ClickZ Today*, May 17, page 1.

InitSatisfaction (2003) "Derived Importance," [http://www.init.satisfaction.net/rubriques\\_uk/techniques/importance](http://www.init.satisfaction.net/rubriques_uk/techniques/importance).

The Business Research Lab (2003) "Interpreting the Results of Your Employee Satisfaction Survey," <http://www.employeesurveys.com>.

Wittink, Dick R., Krishnamurth, Lakshman, Nutter, Julia B. (1982), "Comparing Derived Importance Weights Across Attributes," *The Journal of Consumer Research*, Vol. 8, No. 4, March, p. 471-474.

Wiles, Judy A., (2002), "Derived Importance-Performance Analysis: a Diagnostic Tool for "Main Street" Planners," Volume 6, No. 2, *Academy of Marketing Studies Journal*, p. 141-149.

