Problems With Derived Importance Measures In Brand Strategy And Customer Satisfaction Studies

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ABSTRACT

For many years, marketers have studied the determinants of brand choice for products and services. The most common approach has been to ask respondents to "self-report" the importance of many product/service attributes and benefits in a product-category. It later became clear that in many cases, what respondents said was important was not reflected in their brand choices. To help them overcome this weakness, an indirect measurement approach, called Derived- Importance, became a popular way to assess the influence of attributes/benefits on brand-choice or customer-satisfaction. Many of the "statistics" purporting to measure derived-importance have serious problems; these problems are discussed in this paper.

Keywords: Derived Importance, Product Strategy, Brand Strategy, Customer-Satisfaction Studies, Attribute/Benefit Analysis

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 service (say, a supermarket or a retail bank), researchers ask: "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 a 11-point (0-10) with no anchors. The pair wise correlation between any two of these measures is virtually always .9 or greater - in other words, the different measures are interchangeable.

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, "prices of entry" characteristics tend to be rated high, while intangible, emotional, some would say "irrational" attributes and benefits, tend to be rated low. Yet, practitioners have 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), and other product categories, where the rational traits are 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, 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 correlating (using a variety of tools we'll note later) these ratings with overall preference, buying behavior or satisfaction. This analysis might lead, for example, to a statement such as: we found that "clean stores" have the closest relationship with buying preference for Kroger's or overall satisfaction with this supermarket chain.

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. Several different related methods are

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used to identify this "derived importance" (i.e., the relationship between the degree to which a brand is perceived to have the 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.

By far, the most frequently used of these methods is #1 above - the cross-sectional correlation method , in which an analysis is done based on data collected at a single point in time. This popularity is partly due 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 above.

Basically, by using this cross-sectional correlation method in the brand choice context, many different attributes/benefits are rated by consumers with respect to the degree to which a brand is perceived to have the attribute (e.g., tastes "minty", low price, etc., for a toothpaste; 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 attribute the service provides and an overall satisfaction 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). A half-century later, it is a very common tool employed by practitioners all over the world. A Google search in March 2012 revealed over 750,000 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) ; "Derived Importance-Performance Analysis: A Diagnostic Tool for 'Main Street' Planners" (Wiles, 2002) ; and "Expectations and Perceptions of Service Quality in Old and New-Generation Banks - A Study of Select Banks in the South Canara Region" (Joshua et al., 2005).

Another example is the procedure that was used in the 2001 Consumer Satisfaction Survey, detailing the drivers of satisfaction with the transportation system in Virginia (Center for Survey Research, 2001). It is also the procedure outlined by the Business Research Lab (2003) noted at employeesurveys.com, when describing their technique for "deriving attribute importance with correlation analysis" . Indeed, on its website, The Business Research Lab specifically refers to the technique as "leverage analysis". Its use in the medical survey arena is illustrated on the website of MedicalSurveys.net, in an article entitled, "Measuring What Is Important to Patients" (Combs, 2002). Another use in the medical area is an article by Liang and Shi (2011), which used derived importance metrics to assess the quality of virtual surgical training. The technique's acknowledgment in indicating drivers of customer service was described in "The Keys to Key-Driver Analysis" (Hochster, 2001), where attribute ratings were correlated with the likelihood to purchase. Init-Satisfaction 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 described the same technique in his discussion of "variance markers" in the survey design (Chynoweth, 2003), indicating how a given attribute will be judged important if the characteristic is highly related to overall satisfaction. A comparison of determining importance directly or using derived importance was performed in the travel area, running an experiment with European tourists and illustrating differences in results (Alegre and Garau, 2011). Many specific techniques have been used to find the derived importance values. The most popular (and most likely, the simplest) technique uses cross-sectional correlation analysis. Other techniques (e.g., a variety of regression-related techniques, Beta Coefficients, Jaccard Coefficients, Kano Coefficients or Path Coefficients), yield, essentially, the same basic results. Various articles compare some different techniques; for example, Lautman and Pauwels (2009) compared various techniques to Vector Auto Regression (VAR) models; Pezeshki and Mousavi (2012) compared using regression models with and without making independent variables into dummy variables to assess derived importance. Regardless of the method used or the application area, these "statistics" have serious problems, which will be discussed further.

OBJECTIVES OF THE STUDY

The primary objective of this study is to point out to marketing-research practitioners, a set of serious issues - indeed, potential "traps" - that may plague a somewhat *otherwise-thought-to-be sound study* concerning the derived-importance scores and/or customer-satisfaction scores associated with evaluating attributes and benefits of products and brands. These serious issues can lead to extremely misleading results. These issues, and the reasoning behind them, are discussed in detail in the following section.

METHODOLOGY

The methodology used in this paper is to present examples and discussion based on marketing-research practices of potential misleading conclusions that may result from the lack of understanding of certain ideas and issues that may appear, at first look, to be the foundation of a study that will lead to valid conclusions and guides to product and brand strategy. There are a variety of these types of issues discussed; they are based on real-life experiences that the authors have observed over several decades. The decision to write this paper, the research underlying it, and the actual writing itself took place over the past few years. The examples cited are based on reports the authors had observed during the past decade; the specific brands (and sometimes the products) involved are part of proprietary studies. The authors' argument is not that the results of marketing research studies involving derived importance and/or customer satisfaction are *always* misleading. It is, rather, that they can all-too-frequently be misleading, unless various issues and aspects of the said studies are clearly understood by the users of the results of the study.

DISCUSSION

In this section, the authors present a discussion of many issues concerning derived importance or customer-satisfaction studies that can all-too-easily lead to misleading results concerning product and brand strategy, unless the potential pitfalls of relying on the analysis are understood.

❖ **Cross-Sectional Analysis May Yield Misleading Information :** The first major problem is that cross-sectional analyses cannot be thought of as a substitute for longitudinal analysis, even though virtually all such analyses undertaken today are cross-sectional in nature. 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, 2003a). 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 0.1 (Clancy, 2003b). A more recent work by the Marketing Science Institute revealed that the elasticity coefficient for changes in advertising expenditures with changes in market share is also 0.1. In other words, longitudinal analysis suggests that advertising alone has a very little effect on sales, while the cross-sectional analysis would lead to the conclusion that it is a prime determinant of sales. However, virtually all "derived importance" studies undertaken today are cross-sectional in nature. Interestingly, while Achenbaum (1966) discussed "changes" in brand perception and changes in the 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 analysis may explain (in a large part) why the average ROI of advertising expenditures in both B2B and B2C categories hovers around zero.

In fact, there is no predictable relationship between the cross sectional correlation(s) and the "longitudinal correlation." Suppose that Y = Brand Share, and X = Advertising Expense, and we have n = 10 brands in our study. Suppose further, 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 the 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 ΔY and ΔX 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 yields the following (Y = Brand share; X's = Advertising Expense; the subscripts refer to two successive time periods).

Table 1: Data With High Cross Sectional Correlations And High Longitudinal Correlation					
Y1	**X1**	**Y2**	**X2**	**ΔY**	**Δ X**
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
Source: Authors' Research					

$R_1(Y,X) = 0.980$
$R_2(Y,X) = 0.954$
$R(\Delta Y,\Delta X) = 0.950$
All of these results are high, and each significant at p-value < .0001. The data in the Table 2 yields the following results (Y = Brand share; X = Advertising Expense; subscripts refer to two successive time periods) :

Table 2: Data With High Cross Sectional Correlations And Low Longitudinal Correlation					
Y1	**X1**	**Y2**	**X2**	**ΔY**	**Δ X**
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
Source : Authors' Research					

$R_1(Y,X) = 0.920$
$R_2(Y,X) = 0.992$
$R(\Delta Y,\Delta X) = 0.097$

Here, $R_1(Y,X)$ and $R_2(Y,X)$ are similarly high (with each p-value < .0001), *but $R(\Delta Y,\Delta X)$ is quite low, and not significant, with p-value > 0.75!*
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.
There are two other problems that arise in the use of the (presumably) simple "leverage analysis" approach. The first of these is easily solvable by proper implementation, although in practice (all-too-often), it is not implemented correctly. Sadly, the other problem is NOT solvable.

❖ **Not All Correlations Are Created Equal :** The authors have used the words "correlation" and "cross-sectional correlation" several times. However, just what are the authors correlating with what (with a bivariate correlation), over which cases? 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 the purchase intent for that brand - or the analogous measures for the satisfaction setting). Apparently, the word "correlation" is often taken for granted. In practice, this supposedly simple correlation analysis is conducted in 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 also viewed 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 unimportant to brand choice, or in the satisfaction setting, unrelated to overall satisfaction.

However, the authors now present several examples that illustrate how the above "taxonomy" of interpretations of the derived importance using correlation analysis is faulty. 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 with a potential component of overall satisfaction and a measure of overall satisfaction).

❖ **The Results Of Assessing The Influence Of New Ideas/Innovations :** Consider an attribute that is innovative and a breakthrough, and that no brand currently delivers. This could be fingerprint IDs 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 vitamin combinations in a soft drink on demand, and without any compromise in taste, and so forth. *All* "brands" of banks, or oil companies, or soft drinks, will achieve low scores on the number of attributes each has, while the 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 with reference to brand choice. However, if the attribute is highly appealing (as the ones mentioned above), 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 ratings or new-concept ratings in order to be certain that the appeal of new ideas and innovations is properly understood.

❖ **The Unfamiliarity Of An Attribute To A Responder Can Be A 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. For example, twenty years ago, MRI technology was available in many hospitals, but large segments of the population had never heard of it, or in today's market, not many people are aware of "Taurine", the magic ingredient in Red Bull, which has been one of the fastest growing soft drink brands for years. This is similar to the Innovation example in its arithmetic. *All* brands receive a low score within some sub-groups in the population (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.

❖ **The Potential Problem Of Reverse Causality :** 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), an extensive 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 soft drink company). All big banks, or well-known oil companies, or highly popular soft drinks will achieve a high score on the amount of the attribute each has (since they will be *assumed* to have it, due to their market leadership), while small banks, and less-familiar, smaller oil and soft drink companies receive a low score on the amount of the attribute each has (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 interpretation will be that the attribute is of high importance to brand choice. Yet, if the companies having the attribute took it away, few would care (How many customers do you know who choose a bank because of its insurance offerings, or who choose an engine lubricant due to its website, or a soft drink due to it 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 to be misleading. However, the authors 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.

❖ **Beware of "Price of Entry" Characteristics :** 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 company). 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. Yet, 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 might perform better!

❖ **Accurately Assessing Intangible, Image-oriented Traits Can Be Difficult :** 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 be applied 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 the brands on this dimension (i.e. "attribute") is, in part, because it seems irrational to apply animate descriptions to inanimate objects. Then, 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). Practitioners have discovered over the past three decades that if such a dimension is highly appealing (such an intangible dimension as "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).

❖ **Spurious Correlation Can Be A Major Source Of Misleading Information :** 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 Red and Blue cans 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 (e.g., Pepsi, McDonalds and Bank of America, respectively) get high scores, and small brands (e.g., Fanta and 7-Up) get low scores. Even if only one large brand has the attribute and all other brands do not have the same, the correlation will be relatively high, and the implication is that the attribute is very important. However, if you strengthened the large brand(s) on this attribute, nothing would happen. If you strengthen 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). 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.

❖ **The Problem of Having High Variability In What Different Segments Of The Markets Are Seeking :** Consider an attribute that many consumers "love" (or, perhaps, "strongly approve"), and many of them "hate" (or "strongly disapprove").

Examples would be additive-enhanced foods such as all the products available today, which are enhanced by vitamins, or very fast acceleration in an automobile. Then, brands that have that particular attribute would get a very high purchase-intent score among segments of the population desiring this attribute, and a low purchase-intent score among other 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 approval and disapproval of the attribute, the closer to zero the correlation). Therefore, the mechanical result generated would be that the attribute is unimportant. However, the attribute might be of critical importance, and its criticality goes totally unrecognized. One approach that some researchers have taken to avoid this problem is to employ symmetric desirability scales as opposed to an asymmetric important scale or any derived importance measure (e.g., Clancy and Shulman, 1990).

❖ **The Underlying Problem Caused By The Possibility Of 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 section, 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 a majority of the 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 true 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., no better!) by 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 being 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.

CONCLUSION

There are several managerial implications of this paper. The authors noted that, based on current marketing research literature and practice, using cross-sectional correlation analysis to determine derived importance scores is quite prevalent in practice. This simple-seeming, very prevalent method needs to be examined carefully by marketing managers to ensure that the "right" correlation analysis (among single-moment in time, cross-sectional correlations) is chosen. Managers should study the eight practical examples of situations when the routine application of derived importance measures to attributes would be misleading, and result in the opposite conclusion to good business sense. As mentioned earlier in this paper, the authors have observed (too) many illustrations of these misleading conclusions in the real-world. Marketing managers need to distinguish different ways in which each of the examples works. Innovative attributes, Unfamiliar attributes, and Price-of-Entry attributes illustrated how the correlation could be near zero, but the attribute could be very important. Other examples (e.g., Reverse Causality) illustrated how the correlation could be near 1.0, but the attribute is unimportant. Even among the first set of examples which exemplify how the correlation can be near zero, yet the attribute is 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 Irrationality/Intangibility, another case where the correlation is near zero, but the attribute important, the driver of the near-zero correlation is that not all the brands get the SAME rating, but that the ratings are random, not related to anything identifiable. Several other cases are (in some sense) more subtle, for example, the Half and Half example and the Interaction example.

The authors' overall core recommendation to marketing managers 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 profits!*

IMPLICATIONS FOR MANAGERS/MARKETING PROFESSIONALS

Marketing managers need to realize that 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, avoiding, among other things, the interaction problems cited. The symmetric desirability scale the authors alluded 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 7-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 this profession (i.e., marketing research) is an alternative approach to desirability, importance and derived-importance measures, and provides deep insight into what the issues are which underlie consumer attitudes and behavior in any product category (e.g., Clancy and Krieg, 2007). The authors have seen several (proprietary) instances in which the pitfalls and basic lack of understanding of a variety of issues discussed in this paper have lead to losing marketing strategies in a few cases, involving losses that they were not ever able to be overcome. The authors are convinced that any marketing manager who is aware of the potential dangers discussed in this paper will be “ahead of the game” when it comes to effective and efficient product- and brand-strategy.

REFERENCES

1) Achenbaum, Alvin (1966) . “Knowledge is a Thing Called Measurement.” *Attitude Research at Sea, AMA Monograph*, eds: Lee Adler and Irving Crespi, Chicago, American Marketing Association, pp. 1-31.

2) Alegre, Joaquin, & Garau, Jaume (2011). “The Factor Structure of Tourist Satisfaction at Sun and Sand Destinations.” *Journal of Travel Research,* Volume 50, Number 1, pp. 78-86.

3) Center for Survey Research (2001). “Summary of Results: 2001 VDOT Customer Satisfaction Survey.” *Report of the Center for Survey Research*, University of Virginia, pp. 7-21.

4) Chynoweth, George (2003). “Variance Markers in Survey Design.” http://www.isixsigma.com/library/content/c030922a.asp , accessed February 7, 2012.

5) Clancy, Kevin (2003a). “Five Things You Can Do To Improve Marketing ROI.” presented at the *Association of National Advertisers National Conference,* Los Angeles, CA, October 18, 2003.

6) Clancy, Kevin (2003b). “Methodological Problems in Studies of Customer Satisfaction.” presented at the *American Marketing Association Frontiers in Marketing Conference*, Bethesda, MD, October 20, 2003.

7) Clancy, Kevin, Berger, Paul, & Magliozzi, Thomas (2003). “Illustrations of the Ecological Fallacy in Advertising Research.” *Journal of Advertising Research*, Volume 4, Number 4, pp. 370-380.

8) Clancy, Kevin, & Krieg, Peter (2000). *“Counterintuitive Marketing: Achieve Great Results Using Uncommon Sense.”* New York: The Free Press A Division of Simon and Schuster, pp. 45-60.

9) Clancy, Kevin, & Krieg, Peter (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, pp. 25-44.

10) Combs, Melanie (2002). “Improving Service From the Customer's Perspective: Medicare's Program Integrity Experience.” http://www.medicalsurveys/tips/patient_satisfaction, accessed February 7, 2012.

11) Dalley, Christoper (2007). “Analytics in Competitive Intelligence: Stated Importance vs. Derived Importance.” *Intelligence for Business,* http://primaryintelligence.blogspot.com/2007/06/analytics-in-competitive-intelligence.html , accessed May 3, 2012.

12) Hochster, Michael (2001). “The Keys to Key-Driver Analysis”, *ClickZ Today*, May 17, p.1.

13) InitSatisfaction (2003). “Derived Importance”, http://www.init.satisfaction.net/rubriques uk/ techniques/importance, accessed May 3, 2012.

14) Joshua, A., Moli, V., & Koshi, P. (2005). "Expectations and Perceptions of Service Quality in Old and New-Generation Banks - A Study of Select Banks in the South Canara Region." *Indian Journal of Marketing,* Volume 37, Number 3, pp. 6-11.
15) Lautman, Martin, & Pauwels, Koen (2009). "What Is Important? Identifying Metrics That Matter." *Journal of Advertising Research*, Volume 49, Issue 3, pp. 339-359.
16) Liang, Hui, & Shi, Minyong (2011). "Quality Assessment in Virtual Surgical Training." *Applied Informatics and Communication*, Volume 224, Number 1, pp. 330-337.
17) Pezeshki, Vahid, & Mousavi, Alireza (2012). "Measuring the Importance of Product Attributes And Its Implications In Resource Allocation." *Manufacturing Research,* Volume 7, Number 1, pp. 86-97.
18) Robinson, William (1950). "Ecological Correlations and the Behavior of Individuals." *American Sociological Review,* Volume 15, Number 3, pp. 351-357.
19) The Business Research Lab (2003). "Interpreting the Results of Your Employee Satisfaction Survey." http://www.employeesurveys.com, accessed on May 3, 2012.
20) Wittink, Dick, Lakshman, Krishnamurth, & Nutter, Julia (1982). "Comparing Derived Importance Weights Across Attributes." *The Journal of Consumer Research*, Volume 8, Number 4, pp. 471-474.
21) Wiles, Judy (2002). "Derived Importance-Performance Analysis: a Diagnostic Tool for 'Main Street' Planners." *Academy of Marketing Studies Journal*, Volume 6, Number 1&2, pp. 141-149.