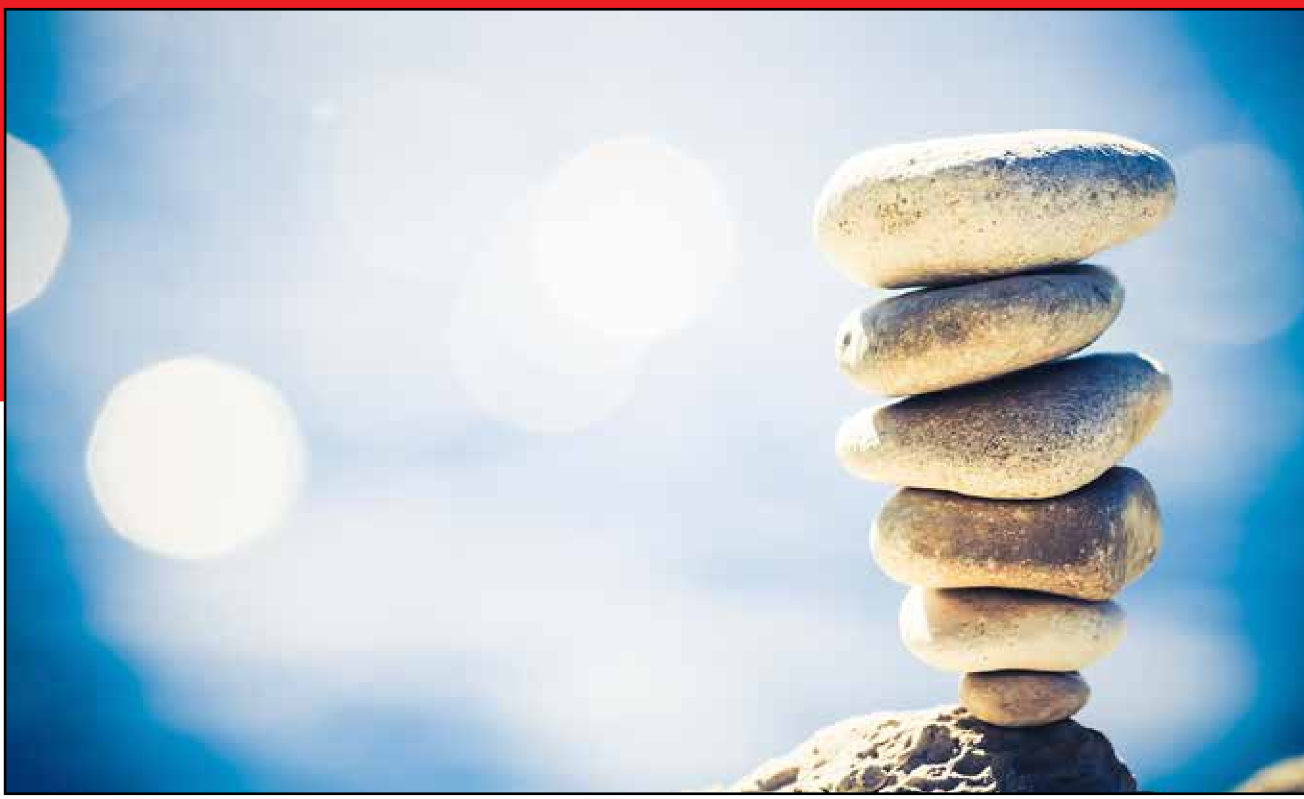
HANSA THOUGHTICLE™

The Strength of Simplicity: Improving Brand Research Results



Although brands often try to position on a few critical pillars, brand surveys commonly seek feedback on a long list of brand attributes. The attributes are often taken from multiple internal stakeholders, each of whom has an interest in some quality of the brand and the corresponding consumers' perceptions. Hence, surveys can sometimes grow to include 15, 20, or even as many as 40 individual brand attributes.

You can imagine the list: trusted, innovative, a leader, high-quality, etc. But like many things in life, more is not always better. With lengthy batteries of brand attributes, respondent fatigue can be a challenge, especially when rating multiple brands. Even in a relatively short survey, rating 20 attributes for 5 brands is tiresome.

Analysis of so many brand attributes leads to greater uncertainty about what is truly important and actionable. Multicollinearity, a statistical problem, confounds our ability to cull from long lists of brand attributes the few factors that really drive brand attraction and preference. More data in this context hides the best answers and leaves decision makers frustrated that we can't tell them what to do.

More data doesn't always mean better answers.

Respondents may also not have a basis for answering about all of these brand details anyway. As a member of a research panel, I received a survey the other day that not only asked me about the usual litany of brand attributes, but did so for brands that I had already indicated I never heard of or only knew the name. (I had to rate them; there was not a "Don't Know" option.) I could have screamed "I don't know!" but the researchers would never know.

In our experience, even when consumers are familiar with a brand, they rarely have a perception of the brand that is as detailed and granular as long lists of attributes assume. An analogy can be drawn between personal relationships and brand perceptions. When consumers experience a brand (products, marketing messages, customer service, etc.), they form a relationship with the brand by a process similar to becoming familiar with another person.

How many relationships do you have that are close enough to judge those people on 20 or 30 traits? Imagine co-workers. You may know that Rafael is friendly, Sandra is trustworthy, and Carlos has a good sense of humor. How much more do you know? Are they good parents? Do they save enough for retirement? Are they neat or messy? What are their favorite foods, sports teams, movies? For most acquaintances and colleagues, what we know about them is far less than what we don't know about them.

Knowing someone that well implies an involved relationship. Yet even casual relationships are likely more important to people than most consumer brands. Simply put, by asking people to rate a brand on an overly long list of attributes, we are asking them not just to tell us their impressions, but to form those impressions as part of taking a survey – to create a relationship on the spot and to conjecture about the brand in that relationship.

Halos may be great assets for angels, but not for brand surveys. Specifically, a halo effect in brand surveys occurs when respondents have a positive impression of one facet of a brand and generalize that positivity to aspects of the brand that are unknown to them. For brand attributes, halo effects occur when consumers' impression of a brand, clear or vague, general or specific, leads to similar responses across an entire list of attributes.

Positive or negative, halos are a reality in brand research.

Keep in mind that if people had a sufficiently concrete impression of the brand for each attribute, the halo would not occur. Instead people would respond based on their existing impressions. Long attribute lists, however, encourage a halo effect by increasing the likelihood that no existing opinion exists for all attributes. The result: respondents rate all of the brand attributes similarly. Put another way, if they know something at a very general level about the brand (good or bad), they will tend to rate each brand attribute as good or bad without making a specific evaluation of each particular attribute.

Of course, another explanation is possible—perhaps everyone in the study has both a detailed view of the brand and happens to feel that the brand is very similar across a wide range of attributes. Logically possible, but not likely, especially with a long list of attributes.

Brand halos are a hindrance for several reasons. One, a halo creates an impression that a brand is doing well (or average or poorly) on some attributes when in fact consumers give very little thought to the brand in that respect. We conclude that people have an opinion and that opinion is positive (or negative) when we should conclude that people have little or no opinion and those attributes are not part of the brand's personality. This problem can be alleviated by allowing "Don't Know" responses although that can lead to other analytical difficulties because of missing data.

Multicollinearity, mentioned earlier, is a favorite topic among researchers. Most people in market research think of multicollinearity as occurring when the predictors or drivers in a regression analysis are highly correlated with one another. Although that's not the strict mathematical definition, it works for our purposes. Because of the halo effect, multicollinearity is nearly ubiquitous in brand research. So what's the big deal?

Multicollinearity can obscure what multiple regression would otherwise reveal.

Using actual data from a recent brand survey, we found an average correlation among 16 attributes of 0.55. (Correlation occurs when attribute ratings move together: when ratings for one attribute go up, ratings for the other attributes also go up.) The average correlation between the attributes and overall impression of the brand was 0.48. Considered one at a time, every attribute had a significant positive correlation with overall impression. Multiple regression analysis tells a different story, however. Only three of the attributes emerged as significant predictors of brand impression.

Of course, the purpose of multiple regression is to tell us what predictors matter because a simple correlation analysis can be misleading. Among other things, regression tells us whether a predictor is significant when controlling for all the other predictors. Therefore, we might be justified in concluding that the analysis did its job, revealing that only three attributes actually predict overall brand impression.

Misfires and missed opportunities can arise when multicollinearity isn't controlled.

Within the market research industry the correlation of .55 among predictors is usually not considered debilitating—somewhat high certainly but not high enough to declare multicollinearity a problem. Other diagnostics tell a similar story. Although we will not go into detail here, those diagnostics say (at least by many published rules of thumb) that multicollinearity is not a sufficient problem to discount the regression analysis. We see it differently.

Again then, what's the big deal? From the data in the example, multicollinearity caused the following:

1. **A potential misfire on next steps.** One of the significant predictors in this study had a negative coefficient. The initial analysis would have us believe that an attribute that is significantly positively correlated with all of the other predictors and with the outcome variable, overall impression, actually has a negative impact. Imagine saying the more trustworthy, or friendly, or interesting I find someone the less I like them. It doesn't make sense and in this case, leads us to believe that multicollinearity is a problem that should be addressed.

2. A greater risk of missing meaningful predictors of brand impression. Multicollinearity increased the confidence intervals around regression coefficients (as is always the case). That is, regression coefficients have greater variance and are therefore less likely to be statistically significant. We may be overlooking important drivers of brand strength as a result of throwing too much in the

analytical pot.

Methods exist for addressing multicollinearity. Some analytical tools are designed specifically to handle multicollinearity (for example, Shapley analysis) or to reduce it (e.g., factor analysis and combining attributes into fewer, multi-item variables). In some contexts, those alternatives are useful or even preferable to reducing the attribute list.

Simple, focused attributes work best in brand research.

Generally, however, multicollinearity leads to unstable estimates and weakens brand research findings. Adding sample to an existing study or repeating a study at a later date can lead to wildly different results even though the underlying relationships are unchanged. In such cases, multicollinearity can lead to different conclusions, different action plans, or a focus on different brand attributes, not for meaningful reasons but because of issues with the analysis.

In sum, we believe lengthy lists of brand attributes and corresponding multicollinearity are a significant problem in market research, and one that can be reduced by using shorter, more focused attribute lists. Shorter lists tend to lead to less redundancy and overlap among the attributes, less halo, lower respondent fatigue, and thus better data. The brand study can then provide greater clarity on what the brand stands for in the eyes of the consumer today, and what actions will most improve the brand in the future.