NAXION thinking

View point

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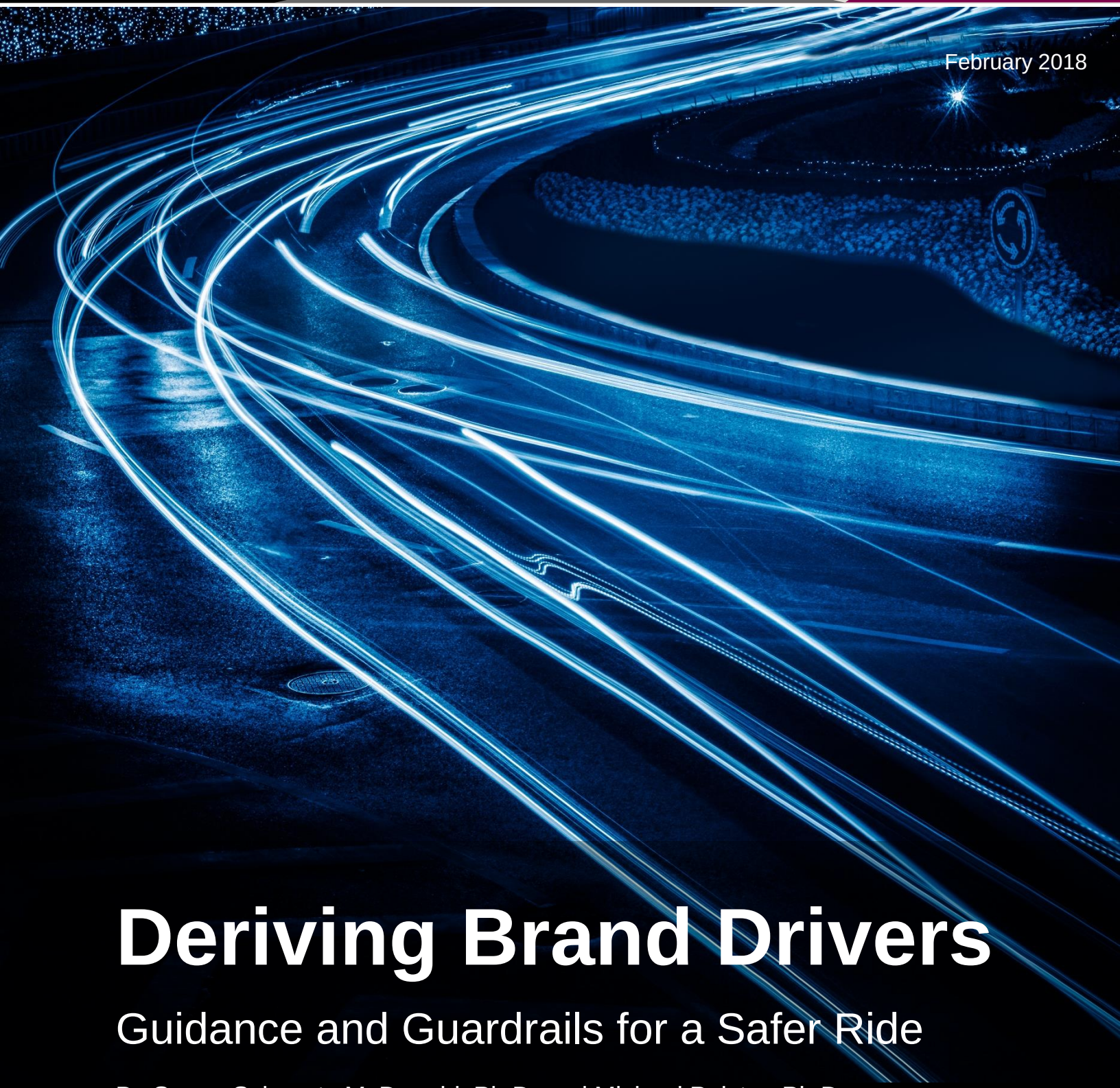


Deriving Brand Drivers

Guidance and Guardrails for a Safer Ride

By Susan Schwartz McDonald, Ph.D. and Michael Polster, Ph.D.

The ‘Quantum Mechanics’ of Brand Decisions

Because some of the drivers of purchase decisions and brand affinity elude consumer self-awareness, “insights research” struggles with a set of fundamental questions: How much can we trust what people tell us about their behavior as consumers when we ask them directly, and if not, are there better ways to measure the “quantum mechanics” that drive brand choice using inferential statistics? In the world of particle physics, we detect the presence and influence of unseen forces by measuring their effects on other things we *can* see. In the world of brand measurement, there can be value in doing the same.

Probing the Mind of Consumers: Whom Should You Trust?

The term “driver analysis” is frequently used to describe a family of statistical techniques – most of them regression-based -- that aim to derive the importance of key decision factors by relating consumer brand assessments to other brand performance metrics. For purposes of this discussion, we are going to exclude conjoint, a special instance of derived importance analysis that is more typically used to guide product development efforts than to assess existing market-place brands. Regression-based driver analysis requires two key data ingredients: (1) Input ratings of brands on a series of attributes and (2) an outcome measure we would like to predict – for instance, brand affinity scores or purchase behaviors. The presumption is that when we have those two types of data available, we don’t necessarily need to ask people to tell us what matters to them when they make purchase decisions. We can infer it.

Lies (or Mistruths) and Statistics

The results of derived importance analysis often match consumers' own "stated: (explicit) ratings of importance — but when the two diverge, there is a tendency to give priority to the derived analysis on the assumption that what we infer about consumers is always more revealing than what they can, or are willing, to tell us. The challenge with that assumption – i.e., our impulse to view statistical analysis as an "infallible" lens on human motivation – is that driver models are, themselves, subject to distortion and error. As a result, driver models may not only fail to lift the veil on customer motivation; they can actually obscure or misrepresent it if we are not careful users of these techniques.

So Where Can Drivers Run Off the Rails?

Several hazards can afflict derived importance, some of which may be addressed with skilled use of specialized statistical techniques and of others which require astute understanding and interpretation of the market context.

Certain market structures and data patterns do not lend themselves to elucidation of drivers via regression.

The characteristics of the brand set you choose will have a powerful influence on driver outcomes. To detect the importance of a driver, it is essential that consumers perceive some difference among the various brands on that dimension because variance is the fuel of a driver model − the ingredient it requires to infer relevance. In some markets, however, brands may receive parity scores on very important attributes. In pharmaceutical markets, competing drugs are sometimes perceived as equally effective, for instance; and in consumer markets, certain price-of-entry attributes may not differentiate key competitors. Anyone trying to take stock of the importance of such attributes via regression would find them statistically “invisible”. Market newcomers looking at very small coefficients might be tempted to underestimate their importance, and even established brands might be tempted to slack off.

Ultimately, the brand set in a driver model needs to reflect your marketing questions and your market perspective. How do you define your competition? What’s the marketplace structure and your marketing strategy? Are you trying to be a game-changer or disrupter who up-ends consumer assumptions about the competitive set? Or are you looking for subtle gradients of competitive advantage over close competitors on low-priority attributes? Driver analysis, like all research, must be both pragmatic and hypothesis-driven. If it’s unlikely to detect something that seems intuitively important, rethink your choice of tools.

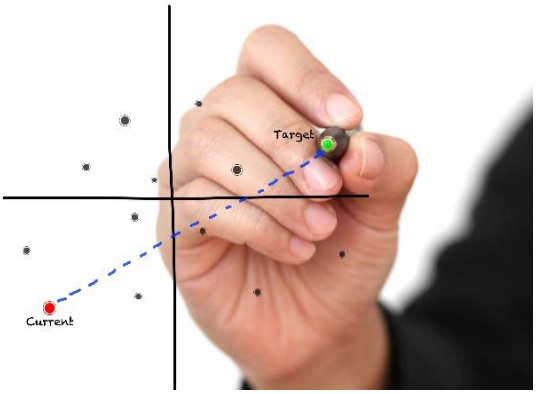
Driver models cannot test for the importance of unrated product or brand dimensions.

This proposition is not as absurdist as it may seem. Just as we have no insight on the stated importance of an attribute without asking, we have no ability to derive the importance of a product attribute through regression unless we have asked respondents to rate products on that attribute. The catch here is that the intuitive appeal of derived importance isn't based merely on the assumption that consumers may not be candid with us when we ask them about their priorities. It also reflects the view that decisions and preferences are significantly influenced by the reflexive "System 1" – emotional reactions that consumers are barely aware of. As it happens, studies supplying data for driver analysis don't necessarily include these metrics. At NAXION, we are experimenting with techniques for implicit association measurement that tap System 1 reactions, but there is a lot of work to be done before these approaches ever earn a routine role in driver analysis.

Regression coefficients — and the differences between them — are not always significant or meaningful, creating a challenge for marketing interpretation.

There is more to identifying drivers than just deriving regression coefficients and ranking attributes on the basis of coefficient size. We need to pay attention to the actual size of those coefficients, and if we are looking at relative priorities, we need to consider whether the deltas actually qualify as meaningful. Conventional methods for determining statistical significance cannot always be applied to driver models so it's sometimes difficult to make confident statements about what matters most to consumers. A driver

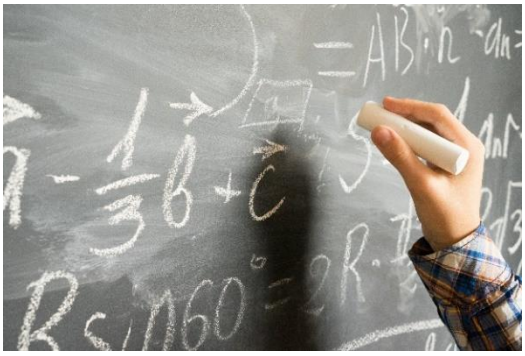
analysis may identify few statistically significant drivers or uncover nothing we couldn't have seen with stated importance metrics. Results like that are disappointing but not, *per se*, a sign of "failure" or improper analysis.



In a quest for meaningful outcomes, quadrant methods for depicting the results of driver analysis, can compound the interpretation problem by creating artificial and misleading distances between attributes that are of equal importance. If attributes below the mean are plotted in a lower quadrant, people may be led assume that those attributes are substantially less important when, in fact, there may be very little statistical separation. You need to be careful in both interpretation and socialization of the data.

A key obstacle to discerning meaningful differences is the problem of *multicollinearity,* which can mask potential driver effects and exaggerate others.

Many derived importance analyses rely on regression-based or structural equation models (SEM) to uncover the role of specific drivers, and all of these approaches are vulnerable to multicollinearity — effects that all appear to march in the same direction but which may not all be equally important, sometimes not important at all. Even SEM is not immune to this problem; it is a technique that aggregates effects more successfully than it parses them. The moral here is that standard SEM is not a panacea. Carefully customized approaches are needed to shore it up.



Like all regression-based models, derived importance techniques are all prone to fallacies of causal interpretation.

We'd be remiss if we didn't acknowledge that driver models can't demonstrate causality — only correlation. Consumers' propensity to rationalize their purchase decisions ("*Product A must offer good value because I bought it*") is an instinct that may further exacerbate multicollinearity, making authentic drivers difficult to isolate. To be fair, though, in the case of driver analysis, we seem more vulnerable to *mis*measurement of relationships (insensitivity or overinterpretation of driver importance) than we are to *mis*interpretation of the *direction* in which relationships move.

Bottom line: driver analysis is an indispensable tool for understanding what draws customers to brands but effective use requires skill and care. There is no room in this field for a robotic approach to statistical calculation that simply defaults to "what the numbers say." Driver analysis is not about received wisdom; it's about critical thinking.

Ten Safe-driving Tips to Keep in Mind

1 **Start with a clear view of how driver analysis works so that you can be prepared to manage pitfalls and mitigate risks. It's not a generic, one-size- fits-all technique. Your choices matter.**

2 **Be as careful in developing attribute batteries as you are in analyzing results. Sound driver analysis should reflect hypotheses about all potential drivers – emotional and rational.**

3 **Choose outcome measures carefully, and whenever possible, include "objective" brand performance metrics like sales.**

4 **Be mindful that choice of competitive set will have enormous implications for driver model outcomes, since each model is fit around specific variance patterns.**

5 **Don't ignore stated importance, especially in markets where customers are trained to be rational decision-makers (e.g., B2B or Healthcare). Customized models can take them into account.**

6 **Choose analytics carefully and be prepared to customize. When dealing with complex, highly intercorrelated attribute lists, consider specialized techniques that avoid the risks of multicollinearity in routine regression models and standard SEM.**

7 **Don't automatically assign greater credibility to derived importance than to stated importance when the two are at odds. Consumers are prone to errors of self-awareness; models are prone to errors of their own.**

8 **Be mindful of statistical and marketing significance in imputing driver importance. Slender effects shouldn't necessarily be seen as powerful insights just because you've dug deep to find them.**

9 **When socializing model results in an organization, be sensitive to the ways in which "effective" graphic displays of driver data can distort and misrepresent results.**

10 **As always, interpret results through the lens of market context to avoid misinterpretation or overinterpretation.**

About NAXION

NAXION is a broadly resourced, nimble boutique that relies on advanced research methods, data integration, and sector-focused experience to guide strategic business decisions that shape the destiny of brands. The firm is distinguished by a truly effective synthesis of authoritative market research and consultative marketing application, and a dedication to solving problems in ways that are both inventive and pragmatic. NAXION's hybrid "enterprise DNA" is rooted in our origins as the world's first business intelligence firm and subsequent decades as the National Analysts division of Booz•Allen & Hamilton. And our exceptional commitment to partnership reflects a unique, employee-owned organizational culture scaled to provide highly effective solutions to clients' most challenging marketing problems.

About the Authors

As enterprise leader and marketing practitioner, Susan has a well-established reputation for guiding development and commercialization of new products, especially paradigm-changing technologies that require new ways of thinking about market structure. Her practice currently focuses on healthcare but she also has decades of experience in consumer products ranging from food and beverages to lifestyle and technology. Susan regularly gives expert testimony in Federal Court on the measurement of brand and trademark strength, and factors promoting or diluting strong and distinctive brand identity. The coauthor of a landmark text on qualitative research methods, she writes frequently on industry topics. Her early professional years were spent as a journalist and poet. Susan holds MA and PhD degrees from UPenn's Annenberg School for Communication, and a BA from Smith College.

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Michael designs and oversees commercial strategy assignments in the Health & Life Sciences practice at NAXION. His methodological expertise, analytical skills, and decades of commercial experience enable him to provide critical decision support to clients seeking to launch and manage brands throughout their lifecycle. Michael also provides intellectual leadership in the firm on a diverse set of topics ranging from neuromarketing to health economics and regulatory compliance, and has published articles in peer-reviewed journals on patient response to DTC advertising messages and other important industry issues. Michael earned a PhD in Experimental Psychology from Cambridge University after completing a BA from Emory University.

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