Potential, stickiness and lift:

how consumer attitude dynamics drive marketing's sales impact

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Abstract

Marketing managers often use consumer attitude metrics such as awareness, consideration and preference as performance indicators because they represent their brand's health and are readily connected to marketing activity. However, their translation into sales performance is insufficiently established to allow financially focused executives to value marketing's contribution and make sound resource allocation decisions. We propose four criteria – potential, responsiveness, stickiness and sales conversion – that connect marketing actions, attitudinal metrics, and sales outcomes. Building on consumer involvement theory, we formulate hypotheses on how these criteria operate differently across conditions of high versus low involvement with the product category..

We test our approach with a rich dataset of monthly marketing actions, attitude metrics, and sales for several consumer brands in two categories over a seven-year period. The results quantify how marketing actions affect sales performance through their differential impact on attitudinal metrics, as captured by our proposed criteria. As predicted, high consumer-involvement conditions require brands to shift consumer attitudes, while low-involvement conditions allow temporary sales hikes without a meaningful attitude shift. Based on these insights, we provide specific recommendations on marketing allocation for different brands, and we validate them in a hold-out sample. For managers and researchers alike, our criteria offer a verifiable explanation for changing marketing elasticities and a tangible connection between marketing and financial performance metrics.

Introduction

Brand managers are urged to compete for the 'hearts and minds' of consumers and often collect *brand health* indicators such as awareness, liking, and consideration to this end. These indicators serve as diagnostics for brand health and help understand the state of mind of consumers. More bottom-line oriented managers, in contrast, typically assess marketing effectiveness at the observable transaction level, with measures such as "advertising elasticity" and "return on sales." This practice obviously satisfies managers focused on financial return (including the CFO), but it leaves the deeper reasons for marketing success or failure unexplored. As a result, past sales impact may not be the best predictor of future sales impact. .

In theory, brand health indicators are predictive of later marketing and bottom-line performance, but this connection is poorly understood. In addition, marketers currently have little guidance on how a better understanding of this connection can be translated into improved resource allocations. How actionable is it, for instance, to know that brand awareness stands at 70% while brand liking stands at 40%? Conventional wisdom suggests investing in the 'weakest link', i.e. the metric with the most remaining potential. However, brand liking may have hit its glass ceiling at 40%, while momentum in awareness may still be possible. In addition, awareness could be more responsive to marketing actions than brand liking, and any gains in brand liking may be short-lived due to fickle consumers or tough competitors, while gains in awareness could be longer-lasting. Finally, awareness gains may convert into sales at a higher or lower rate than liking gains do.

In sum, it is no small task for brand and marketing managers alike to use consumer attitude information to guide their marketing strategies and actions. Our main objective is therefore to provide concrete directions on how marketing effectiveness can be improved by examining attitude metrics. More specifically, we introduce a model that connects marketing actions, attitude metrics and sales and we propose a set of criteria to translate the diagnostic analysis of attitude metrics into concrete recommendations for resource allocation. By applying these criteria we can determine the marketing investment appeal of each marketing instrument. We validate our approach empirically on brands from two consumer good categories and demonstrate that a better understanding of the connection between marketing actions, consumer attitudes, and sales leads to better sales forecasts. A second validation consists of a comparison between the two categories because they represent different levels of product involvement, one of the most studied factors affecting consumer behavior.

Although this research topic is at the core of the study of marketing strategy effectiveness, it has received little coverage, mainly because the right combination of data sources has been lacking. Data on consumer attitudes, marketing actions and marketing performance may be available, but the connection between all three types of variables is rarely made. For our demonstration we use data on all three types of variables, measured at the same observation level (the brand) with the same periodicity. Although such data sources are unusual in current practice, they are likely to become more commonly available in future via the internet.

We begin by introducing a conceptual framework around the role of attitude metrics in consumers' purchase processes. Next we explain how this role differs across different brands and products. We then propose four criteria for the analysis of attitude metrics. In the empirical section we demonstrate how the relevant parameters can be estimated, and apply these criteria, first for a diagnostic analysis and then for a forward-looking analysis.

The Influence of Consumer Attitude

Our fundamental premise is that the analysis of *intermediate attitude performance metrics* allows us to explain and quantify the observed differences in marketing effectiveness across brands and over time. Recently, Srinivasan, Vanhuele, and Pauwels (2010) showed *that* attitude metrics explain sales performance over time in a sales model that already accounts for the direct effect of marketing actions. However, in order to reach our objective to give directions about marketing spending, we also have to understand *how* attitudes influence sales. In addition, we need to understand the connection between marketing actions and attitudes.

Our conceptual framework, displayed in Figure 1, contrasts marketing effects that occur through changes in attitudinal metrics with those that occur without such changes. We denote the former as the ‘mindset effect’ and the latter as the ‘transaction effect’ in Figure 1. We do not propose that purchases occur without the customers’ minds or hearts being involved (e.g., one needs to be aware of a brand at least right before buying it), but instead that customers may simply react to a marketing stimulus without changing their mind or heart (e.g. the brand was in the consideration set before, and remains in the consideration set after a stimulus-induced purchase). Our framework therefore accounts for both generally accepted channels of marketing influence: through building the consumer attitudes that constitute the brand’s health and/or through leveraging the brand’s existing health.

-- Insert Figure 1 about here ---

Obviously, the extent to which attitude metrics affect sales will vary across brands and products, because consumer behavior can differ across different products and brands. An important question is therefore to what extent attitudes translate into purchase behavior (Berger and Mitchell, 1989), which we refer to as “sales conversion”. To test our understanding of these attitude dynamics, we will focus on a dominant factor influencing consumer behavior, product involvement, and we will compare sales conversion for high vs. low-involvement purchase situations.

Product involvement is generally understood as referring to the personal relevance of the object based on inherent needs, values and interests (Zaichkowsky, 1985). The Elaboration Likelihood Model (ELM) holds that a critical factor driving enduring persuasion (for instance by advertising) is whether an individual is motivated to elaborate on, or think about, a potentially persuasive message (Petty and Cacioppo, 1979). One of the most important determinants of elaboration motivation is involvement (Petty et al., 1983).

How is product involvement relevant for the conversion of attitudes to behavior? Nelson (1970) developed an economic perspective classifying a brand purchase decision as either low involvement, where trial experience is sufficient, or high involvement, where information search and conviction is required prior to purchase. Thus, when product involvement is high, a product or brand needs to change consumers' hearts and minds in order to change their purchase behavior. The perceived risk of changing (purchase) behavior needs to be overcome in the consumer's mind (Bauer, 1967; Peter and Tarpy, 1975). In contrast, when product involvement is low, consumers may buy a product simply because it is available or promoted, without having fundamentally changed their opinion about it. This low-involvement path is compatible with Ehrenberg's awareness-trial-reinforcement model (1974).

In the context of our research, we distinguish two involvement scenarios:

1) High involvement implies that attitudes and product buying decisions are driven by stable, deeper meanings associated with consuming these products (e.g. Fournier 1994). In these conditions, we expect movements in attitudinal metrics to be strongly associated with sales, i.e. there is sales conversion.
2) In low-involvement categories, consumers do not give much thought to their purchase decisions in the category. As a result, we expect low sales conversion. Marketing actions may have a direct impact on sales without affecting the attitudinal metrics, called the "transaction effect" in Figure 1. Many frequently purchased consumer packaged goods fall within this category, and several studies have demonstrated this type of choice behavior (e.g. Hawkins and Hoch, 1992).

Relevance Criteria for Customer Attitude Metrics

To move from an analysis of attitude metrics to recommendations for marketing resource allocation, we have to identify the relevant attitude metrics. A relevant attitudinal metric is one that has a long-term or equilibrium association with sales performance, meaning there is long-term *sales conversion*. For example, it must be true that, all else equal, higher brand awareness is associated with higher sales performance. The equilibrium sales conversion of an attitudinal metric is empirically testable, as we will demonstrate below.

Sales conversion is a necessary but not sufficient condition for an attitude metric to contribute to marketing's long-term impact on sales. For any given brand situation, the metric must also have *potential* and *staying power*, and must *respond* to marketing actions. For example, if the relevant metric "brand awareness" is low, is responsive to brand advertising, and stays at higher levels after advertising stimulation, then a firm's advertising campaign that is aimed at increasing this particular attitudinal metric is likely to have a sizeable and long-lasting sales impact. Conversely, if brand awareness is high, unresponsive to advertising, and quick to decay, the same advertising campaign will likely have a much smaller and shorter-lived sales effect. We now examine these three criteria in turn.

Potential as a driver of marketing impact has long been appreciated and used, especially in the context of *market* potential (e.g. Fourt and Woodlock 1960). The central premise is that of diminishing returns, i.e. the larger the remaining distance to the maximum, the higher the impact potential. Fourt and Woodlock applied this principle to new-product penetration forecasting and found that penetration evolves as a constant fraction of the remaining distance to the maximum. Thus if awareness impacts new-product trial, then, all else equal, marketing spending aimed at awareness building will have more impact potential if the beginning awareness is 20% as opposed to 70%.

Stickiness or *inertia* refers to the *staying power* of a change in the attitudinal metric, in the absence of further marketing effort. For example, if consumer memory for the brands in a category is long-lasting, it will take little or no reminder advertising for a brand to sustain a recently gained increase in brand awareness. Similarly, if consumers in a category exhibit strong *habits* and routinely choose among a subset of the same four brands (i.e. the evoked set), then the consideration metric for any of these four brands may be sticky. Overall, if a marketing effort increases a brand's score on a sticky attitudinal metric, then all else equal, that effort is more likely to have a long-run impact on business performance.

Responsiveness or *lift* refers to marketing's ability to "move the needle" on the attitude metric. In this context, different marketing actions will likely have different responsiveness. For example, advertising is known to be better at inducing trial purchases than repeat purchases (Deighton, Henderson and Neslin 1994), so an awareness metric may be more responsive to it than a preference metric. Responsiveness is also related to environmental conditions, especially when the market space is cluttered (Danaher, Bonfrer and Dhar 2008). For example, with limited retailer shelf space, an abundance of offerings in a category limits the power of trade incentives to gain shelf space.

Metrics and Models

Modeling the dynamics of attitudinal metrics requires an operationalization of potential, stickiness and responsiveness as well as their conversion into sales. We review these in sequence.

Potential (POT_t) is the remaining distance to the maximum, preferably expressed as a ratio in light of the multiplicative nature of market response. For example, if maximum awareness (MAX) is 100% and current awareness Y_t is 30%, then

$$POT_t = [\ MAX - Y_t\ ] / MAX = 0.7. \tag{1}$$

Most consumer attitude metrics are expressed in percent (MAX=100%) or in Likert scales (e.g. 1 to 7, MAX=7), both of which readily accommodate our proposed definition of potential.

Stickiness (ST_t) or *inertia* is the degree to which a change in the level of a metric is upheld over time, absent any new stimuli. This can be modeled by a simple univariate AR(p) process on the attitude metric, where stickiness is quantified as the sum of the AR coefficients (e.g. Andrews and Chen 1994). For example, if the simple AR(1) model represents the over-time behavior of the attitude metric Y, i.e.

$$Y_t = c + \varphi\, Y_{t-1} + \varepsilon_t \quad \text{, where } \varepsilon_t \text{ is white noise,} \tag{2}$$

with parameter φ=.6, then stickiness = .6. This means that 60% of any shock in Y_t is carried over to the next period. Similarly, if the univariate model is AR(2) with parameters $\varphi_1 = 0.6$ and $\varphi_2 = 0.15$, then stickiness = .75. A priori, we expect consumer attitudinal metrics to be stationary, i.e. the sum of the AR parameters is less than 1 because of memory decay effects that are well-documented in psychology (Baddeley, Eysenck and Anderson, 2009).

Stickiness is important because it identifies the long-run impact of a movement in an attitude metric. For example, with φ=.8, if the metric increases from 10% to 15% due to a marketing initiative, the 5% gain in one period will result in total gains over time of 5%/(1-.8) = 25%. If stickiness were 0, the gain would only be the one-time lift of 5%.

Responsiveness or *lift* is the short-term response of the attitude metric with respect to a marketing stimulus. We propose to use well-established, robust response functions to estimate responsiveness. For example, the standard multiplicative response model produces elasticities as responsiveness metrics:

$$Y_t = c\, Y_{t-1}^{\gamma}\, X_{1t}^{\beta_1}\, X_{2t}^{\beta_2}\, X_{3t}^{\beta_3}\, e^{u}{}_{t} \qquad (3)$$

where Y is an attitude metric and X_i (i=1,2,3) are marketing instruments. Not only do such response models provide readily interpretable results, they have also been shown to outperform more complex specifications in forecasting product trial for consumer packaged goods (e.g. Hardie, Fader and Wisniewski 1998).

Note that responsiveness may be related to potential as follows: the closer the attitude metric is to its ceiling value, the more difficult it will be to register further increases through marketing. That phenomenon is readily incorporated in (3) by expressing the dependent variable as an odds ratio (e.g. Johansson 1979):

$$Y'_t = Y_t \,/\, (MAX-Y_t) = c\, Y'^{\gamma}_{t-1}\, X_{1t}^{\beta_1}\, X_{2t}^{\beta_2}\, X_{3t}^{\beta_3}\, e^{u}{}_{t} \qquad (4)$$

where the response parameters β_i now indicate either a concave ($\beta_i < 1$) or an S-shaped ($\beta_i > 1$) response curve. The resulting response elasticity η_i is now contingent on the attitude metric's potential as follows:

$$\eta_i = \beta_i * POT_t \tag{5}$$

For example, in an awareness-to-advertising relationship with a response elasticity 0.2 at zero initial awareness, the response elasticity will decline to 0.2*0.6 = 0.12 when awareness reaches 40%.

Marketing investment appeal. The product of potential, stickiness and responsiveness is an ex-ante measure of the appeal of the attitudinal metric for marketing investments. For example, all else equal, the higher the potential and stickiness of brand awareness, and the more responsive it is to advertising campaigns, the more the brand manager can justify investing in advertising. However, marketing investment appeal is also determined by the degree to which the intermediate performance metric awareness is related to financial performance, i.e. sales revenue. We have previously referred to this as the *conversion* factor.

Conversion is the degree to which movements in the attitudinal metric convert to sales, similar to a conversion rate of leads into customer orders in B2B. Conversion rates are typically well below unity; for example Jamieson and Bass (1989) reported ratios of stated vs. actual consumer trial in ten product categories ranging from .009 to 0.896, averaging around 0.5. When historical data are available, conversion metrics may be estimated from a “funnel” model, with upper-funnel metrics such as awareness and lower-funnel metrics such as preference or liking. However, we do not want to impose a hierarchy-of-effects, because there is little support for such hierarchies (e.g. Batra and Vanhonacker 1988). Instead, we allow for a multiplicative funnel model that can be applied across conditions. For example, with intermediate attitudinal metrics awareness (A_t), consideration (C_t) and liking (L_t), a multiplicative funnel model for sales revenue (S_t) would be

$$S_t = c\, S_{t-1}^{\lambda} A_t^{\beta_1}\, C_t^{\beta_2}\, L_t^{\beta_3}\, e^{u_t} \qquad (6)$$

Conversion models such as (6) can be tested either with longitudinal or with mixed cross-sectional time-series data. Before we move to the empirical section, we first illustrate the usage of these different criteria to calculate marketing investment appeal.

Illustrative Example

Consider two brands, A and B, in a product category. We would like to compare marketing investments in price promotions versus advertising with respect to the attitudinal metrics awareness and consideration. Existing statistical models such as (4) reveal that awareness is more responsive to advertising, and consideration is more responsive to price promotion. The brands’ starting conditions are listed in the first line of the table below:

	AWARENESS		CONSIDERATION		SOURCE
	BRAND A	BRAND B	BRAND A	BRAND B	
Beginning level	.8	.3	.4	.5	Data
Potential	.2	.7	.6	.5	Equation (1)
Stickiness	.9	.9	.5	.5	Equation (2)
Response to promotion	.01	.035	.18	.15	Equations (4)(5)
Response to advertising	.04	.175	.06	.1	Equations (4)(5)
Sales Conversion	.15	.2	.4	.5	Equation (6)
Marketing Investment Appeal					
promotion	.015*	.07	.14	.15	Equations
advertising	.06	.35	.048	.10	(5)(2)(6)

* Appeal equals the product of potential, stickiness, response and conversion for each attitude metric, summed up over attitude metrics.

These scenarios imply different marketing resource allocation prescriptions for the two brands. For example, both brands should favor advertising to increase awareness (higher response). However, because of differences in their potential, brand B stands to gain more from such investments. Furthermore, when considering the sales conversion factors, we can compare the long-term sales impact potential of each marketing investment for each brand. For example, sales promotion investments are more appealing for Brand B, and advertising is more appealing for Brand A. Of course, determining the most suitable investment levels will require information on profit margins and other considerations as well.

Empirical Study

At this point, we introduced a model of how marketing actions, attitude metrics, and sales are connected. A first goal of our empirical section is to apply this model to a relevant data set and check the validity of the results and their usefulness for the diagnosis of brand health. We expect the results to vary across products and brands and want to benefit from this variation to test our understanding of the attitude dynamics by comparing a high with a low-involvement category. We also make ad-hoc comparisons between high and low-priced brands.

In addition, we aim to provide guidance to decision makers for their allocation decisions. We therefore have as a second goal of the study to establish predictive capability of our overall model by demonstrating that the use of attitudinal metrics significantly improves the accuracy of sales outcome predictions in function of planned marketing expenditures. We reserve a hold-out sample for this purpose.

A third goal is to demonstrate how our approach is useful for allocation decisions. We first show how the inputs for the calculation of marketing investment appeal are estimated from the data. We then demonstrate how strategic implications can be derived from the results and we conclude with a simulation of different spending scenarios.

Data

The data come from a brand performance tracker developed by Kantar Worldpanel, which reports the marketing mix, mindset (based on 8,000 households) and performance metrics across brands in each category on a four-weekly basis. The details on these data sources are described in Srinivasan, Pauwels and Vanhuele (2010).

For the period between January 1999 and May 2006, we analyze data for the leading brands of bottled water (4 brands) as example of a low-involvement category and shampoo (6 brands), as example of a high-involvement category. The focal brand performance measure is sales volume[1] aggregated across all product forms of each brand (in milliliters). The marketing mix data include average price paid, value-weighted distribution coverage, promotion, and total spending on advertising media.

After discussion with the data provider, we selected the following three measures from the available attitudinal metrics: advertising awareness, inclusion in the consideration set and brand liking. This selection aimed at covering the three main stages of the purchase funnel. Two other available measures were not included due to lack of variation (aided brand awareness) or collinearity ("intention to purchase" correlated highly with consideration set, and the data provider considered the latter to be managerially more useful).

For advertising awareness, survey respondents indicated, in a list of all brands present on the market, those for which they "remember having seen or heard advertising in the past two months." Our measure gives the percentage of respondents who were aware. Liking is measured on a seven-point scale (from "like enormously," to "not at all"), and the measure we use is the average rating. For the consideration set, respondents were asked to indicate "the brands that you would consider buying" from a list of all brands in the market. We use the percentage of respondents who consider buying as measure.

[1] Although the actual measure of brand performance is purchases, as registered by consumers, and not sales, as registered by stores, we use the word "sales" in the remainder of the paper.

With a time sample of more than seven years, the presence of different players with different strategies in different product categories, and wide coverage of the marketing mix as well as consumer attitudinal metrics, these data are uniquely suited to address our research questions. The country of investigation is France, which is more homogeneous than large multi-cultural markets such as the US in terms of consumer behavior and retail industry structure.

Econometrics

The attitude-to-sales conversion parameters are estimated at the category level, with data that are pooled across brands. This provides more efficient parameter estimates relative to a brand-level model. A conceptual argument for pooling is that, while mindset responsiveness to marketing may differ across brands, mindset-to-sales conversion depends mostly on category characteristics, for example liking may convert to sales more in hedonic versus utilitarian categories. Moreover, if pooling is appropriate, it not only provides more degrees of freedom but also can reduce the level of collinearity in the data (Kumar and Leone 1988). Our empirical tests indicated that brand data could be pooled within each of the two categories.

It is important to guard against possibly spurious results due to reverse causality, for example the scenario whereby a brand scores high in awareness because its sales are high. In other words, we must verify that attitudinal metrics are *leading,* not *lagging,* indicators of business performance. We employ a Granger causality test for that purpose, i.e. the attitudinal metric M Granger-causes sales S if the model

$$S_t = f[M_{t-k}, S_{t-m}], \text{ where } k>0 \text{ and } m>0, \tag{7}$$

outperforms the univariate model

$$S_t = f [S_{t-m}] \qquad (8).$$

The lag lengths *k* and *m* in these models are derived empirically using the Schwarz information criterion (see e.g. Hanssens, Parsons and Schultz 2001). Model performance is established on a forecast sample using a standard metric such as root mean squared error (RMSE).

Taken together, the attitudinal metrics, sales outcomes and marketing actions form a system with feedforward and possibly feedback loops. Several econometric methods are available to estimate the relevant parameters, ranging from single-equation models to systems models. In what follows we will tailor the estimation method to the objective at hand and conduct specification and robustness tests as needed.

Results

Due to the large number of empirical results, we report on two major water brands (WA and WB) and two major shampoo brands (SA and SB). The categories represent low and high-involvement products respectively. In each category, brand A is a premium / lower volume share brand and brand B is a low-priced / higher volume share brand. Note that an important marketing variable, distribution, is omitted because all leading brands in this dataset had near-perfect levels of retail availability throughout the sample period.

Brand diagnostics

The collection of the relevant brand diagnostics requires several steps, including data averages (for base levels), univariate time-series models (for stickiness) and market-response models (attitude response, sales response and conversion equations).

Table 1 shows the univariate time-series models on the attitudinal metrics. The univariate models include no more than 3 autoregressive parameters and the model residuals are white noise as indicated by the Ljung-Box Q statistic.

--- Insert Table 1 about here ---

Overall, the stickiness measures for upper-funnel metrics awareness and consideration, as computed by the sum of the AR parameters, are high and range from about 0.5 to 0.8. By contrast, the lower-funnel metric liking is generally less sticky, especially in the low-involvement category (bottled water). For brands WB and SB, there is no noticeable stickiness for liking. Instead, this attitudinal metric behaves as a zero-order process around its mean. Thus the univariate results suggest that changes in liking are stickier for higher-priced brands (WA and SA) than for lower-priced brands (WB and SB).

Table 2 shows the attitudinal response models. Awareness is positively influenced by advertising for all four brands, WA, WB, SA, and SB. Consideration is positively influenced by sales promotion for both SA and WA and negatively influenced by price for WA. Liking is negatively influenced by price for WA. Interestingly, the premium brand in the low-involvement water category (WA) is is negatively influenced by pricing across all attitudinal metrics.

Turning to sales response, if the brand manager had access only to transactional data on sales and the marketing mix, he or she would be able to estimate the standard marketing-mix model (equation (6)) shown in Table 3. The results are fairly typical, with the highest elasticity (in absolute value) for price, followed by promotion and advertising.

--- Insert Table 3 about here ---

We will use this model as a benchmark for comparison against the more comprehensive funnel models in Table 2.

A comparison of Tables 2 and 3 indicates that attitudinal response to marketing is typically lower in magnitude than sales response to marketing, reflecting our argument that some marketing actions may affect sales without a corresponding change in specific attitude metrics. Thus, while changes in attitudinal metrics are important, they are not the only explanations for changes in sales.

Table 4 summarizes the results of the conversion equations. All three attitudinal metrics of awareness, consideration and liking significantly influence sales for the shampoo category. In the bottled water category, only changes in awareness and liking influence sales.[2] These results illustrate differences in response structure between high-involvement and low-involvement categories, as predicted by consumer behavior theory. As postulated, the higher the consumer involvement with the category, the stronger the conversion parameters, as is the case with shampoo. In the other direction, a set of near-zero conversion parameters would imply that most purchase decisions occur regardless of movements in brand attitudes. This could occur when consumers buy on impulse or in function of in-store display and promotion factors. Bottled water illustrates this pattern well.

--- Insert Table 4 about here ---

[2] Granger causality tests revealed that the causality direction was from attitudinal metrics to brand performance for the four brands studied.

Predicting Marketing Impact in a Holdout Sample

The estimates reported in Tables 1-4, based on the 84 initial observations are consistent with our arguments on the role of attitudinal metrics in establishing marketing impact. However, in order to gain managerial relevance, the models need to have predictive validity, i.e. collecting and using information on a brand's attitudinal metrics should allow managers to make better predictions of business performance in function of planned increases, cuts or reallocations in marketing spending in our hold-out sample (observations 85-96).

A comparison of the two data series shows that several brands implemented strategic shifts in their marketing allocations during the hold-out period. For example, shampoo brand A increased its advertising spending by 50%, tripled its promotional spending and kept its prices the same. In contrast, water brand A cut its advertising spend by 42% and increased its promotion spending by 35%, while also keeping prices the same. Whereas both brands are comparable by virtue of their premium positioning, we observe from Tables 1-4 that, at the end of the observation sample (period 84), shampoo brand A had a higher potential and sales conversion for awareness and consideration, and a higher stickiness in all 3 metrics. Because awareness is responsive to advertising, and consideration and liking to promotions, increased spending on these marketing activities should have a strong and lasting impact on sales. In contrast, water brand A’s increased use of promotions is unlikely to have these benefits: promotions only marginally translate into consideration increases (Table 2), which in turn do not significantly raise sales (Table 4).

We compare conditional forecast results for the monthly observations 85-96, where the brand's resource allocations for those periods are known (i.e. planned) at the end of period 84. The benchmark forecasts are drawn from the marketing mix models (without attitudinal metrics) reported in Table 3. The comparison forecasts are obtained from models with both marketing-mix and attitudinal metrics. These models thus allow marketing actions to have both 'transactions' and 'mind-set' effects. The comparisons are based on one-step ahead and multi-step forecasts, i.e. projections up to twelve periods ahead. While the one-step forecasts are expected to be more accurate, the multi-step predictions are more realistic and strategically valuable in a twelve-month marketing planning scenario.

Table 5 shows the comparative results, with a focus on prediction accuracy, as measured by Mean Average Prediction Error (MAPE). Importantly, the sales predictions made by the "marketing mix and mind-set" models outperform the benchmark forecasts in 17 out of 20 cases. As expected, the sales predictions improvements for one-step forecasts are lower since these are more accurate across the board. The average prediction improvement is sizeable, about 28.2%. The sales response model with attitudinal metrics offers superior prediction improvements for the shampoo category as compared to the water category: 27.8% vs. 15.4% for one-step forecasts and 34.6% vs. 30.7% for multi-step forecasts. Overall, the degree to which a model with attitudinal metrics and marketing mix outperforms a straight marketing mix model is greater for the higher-involvement categories, as predicted from consumer-behavior theory.

Brand-level strategic implications

Having established the predictive validity of our approach, we can examine some concrete implications of our results for the focal brands. Our focal **shampoo** brand SA has ample room for mind-set expansion across the board: awareness 27%, consideration 17%, and liking 71% (5 out of 7). All three attitudinal metrics have stickiness of over 0.65, and as a result, the brand's potential in attitudinal space is high. Not surprisingly, the highest sales conversion elasticity (0.462 reported in Table 4) is obtained for consumer liking, about twice as high as for the upper-funnel metrics.

The results for our focal **bottled water** brand WA are different, and in the proposed directions. Stickiness for awareness and consideration are comparable to shampoo, but stickiness for liking is much lower, suggesting that consumer' purchase decisions are closer to a zero-order process (see Table 1). On the other hand, liking is the only attitudinal metric that converts significantly into sales (elasticity 0.517 reported in Table 4). Thus, any marketing effort that stimulates attitude metrics other than liking is likely to have only negligible demand effects. On the marketing-mix side, we find, as expected, that advertising works best in the upper funnel (Table 2). Overall, price is the only variable that has substantial marketing investment appeal.

We illustrate the implications of these results in Tables 6a and 6b for the shampoo and bottled water categories. The tables contrast a hypothetical marketing campaign that quintuples advertising spending (panels A and B) with a campaign that doubles promotional effort (in panels C and D).

--- Insert Table 6a and 6b about here ---

As expected, the promotional campaign would have the highest sales impact (16.8% increase), but that increase is associated with very little mindset movement (only 2.3%) as shown in Panel B of Table 6a. In contrast, the 2.2% sales increase coming from the advertising campaign is predominantly due to mindset movement (1.7%) as shown in Panel A of Table 6a.

The scenario simulation results also support our findings on the effect of involvement (Table 6b). For both advertising and promotion, long-term sales gains occur predominantly from transactions increases. The difference with shampoo is especially striking for advertising: its sales impact for shampoo comes primarily from mindset movements; of the total sales impact of 2.2% due to increase in advertising, mindset movements account for 1.7%. By contrast, for bottled water the pattern is reversed and the sales impact comes primarily from transaction effects.

These findings demonstrate that incorporating the role and the responsiveness of ‘customer's mind and heart' metrics improves our understanding and predictability of marketing impact on sales. As such, this practice can improve the quality of marketing resource allocation decisions for the analyzed brands.

Conclusions

We argued in our introduction that the CFO's needs for financial accountability of marketing may well be met by traditional marketing-mix models on transactions data. However, the CMO also needs to understand the *consumer behavior reasons* why marketing does or does not impact business performance. Our paper has demonstrated that the objectives of both stakeholders can be met by recognizing the unique properties of attitudinal metrics and their relationship to sales performance. In particular, these measures have potential, stickiness and responsiveness to marketing that can be assessed from the data. Furthermore, the *relevance* of these metrics may be assessed by their conversion into sales performance, which provides the critical accountability link with the CFOs needs.

By applying our approach, managers can develop actionable guidelines on how to apply closed-loop learning on the attitude metrics (e.g. “if one observes metrics with the following values/characteristics, then this marketing action will be most effective”).

Different product categories and brands within them vary significantly in the magnitude of these diagnostics, and these differences form the basis for formulating marketing resource allocation strategies that are more likely to succeed (see Table 7). For example, brands that invest substantially in awareness-generating advertising may witness lifts in awareness that do not translate into sales improvements. We label this a “wrong focus” scenario; it applies to water brand WA with respect to advertising and awareness. Conversely, if the attitudinal metric has high sales conversion but does not respond well to increased marketing spending, that would result in a “wrong marketing instrument” scenario. This is the situation that shampoo brand SA finds itself in with regard to consideration and sales promotion.

--- Insert Table 7 here ---

Future research should explore category comparisons with even higher levels of consumer involvement, such as durables and high-value services, possibly using data at different time intervals (e.g. weekly, monthly, quarterly, etc.). If individual-level attitude metrics are available, these could be used in more granular response-model specifications. Moreover, data on the profits gained from better decisions would enable managers to weigh them against the cost of collecting attitudinal metrics, thus providing an ROI measure for such data. Indeed, the need for attitudinal metrics that match the transactional records is a limitation of our approach. Such attitudinal tracking data are typically survey based, which is costly and subject to sampling error. However, the digital age offers new opportunities in this regard. Instead of surveying consumers, one can observe how they express themselves on the internet, via searches, chat rooms, social network sites, blogs, product reviews and the like. Some preliminary evidence suggests that "internet derived consumer opinions" are predictive of subsequent behavior (e.g. Shin, Hanssens and Gajula 2010). Future research should examine which internet-derived attitudinal metrics are the most relevant. These metrics could then be substituted for the survey based measures that were used in this paper.

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Figure 1: Conceptual Framework

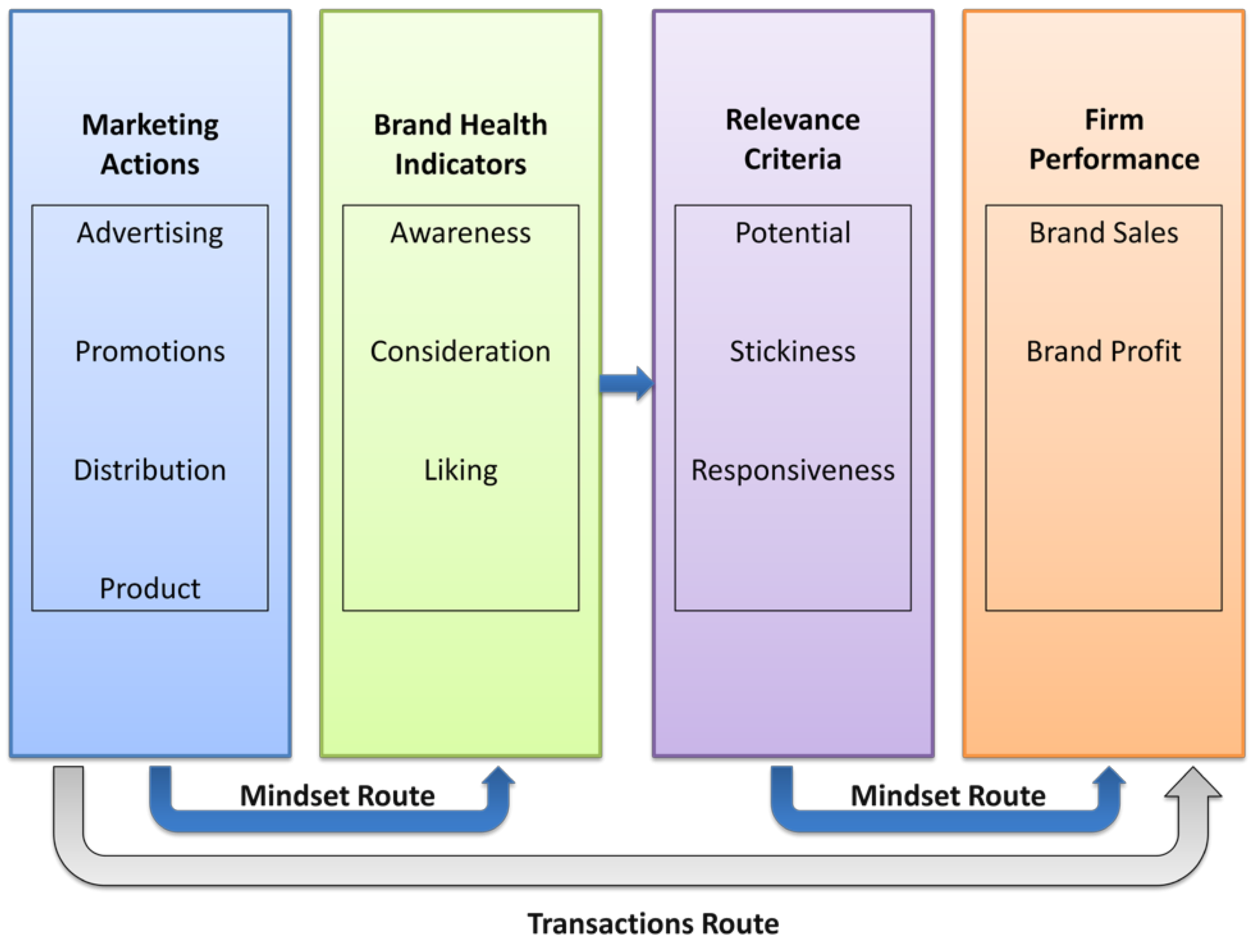

Table 1: Comparison of Present Study with Srinivasan, Vanhuele and Pauwels (2010)

	Srinivasan et al. 2010	***Present Study***
1. Primary Research Objectives		
a. Do mindset metrics even matter in market response models?	✓	✓
b. How do mindset metrics matter in market response models?	--	✓
c. What guidance can this knowledge provide for marketing resource allocation?	--	✓
2. Brand performance outcome metric	✓	✓
3. Mindset metrics - Awareness, Consideration, Liking	✓	✓
4. Marketing actions - Advertising, Price, Promotion, and Distribution	✓	✓
5. Incorporates consumer behavior theory	--*	✓
6. Proposes relevant metrics and criteria for marketing resource allocation	--	✓
7. Data – Kantar World Panel	✓	✓
8. Modeling suited for different methodologies (Model 'agnosticism')	--**	✓
9. Decomposition into mindset effect and transactions effect	--	✓
10. Cross-category evaluation of effects based on consumer involvement	--	✓
11. Decision support focus: provides guidance on marketing resource allocation	--	✓
12. Predictions in hold-out sample of marketing's future impact	--	✓
13. Brand-level strategic implications	--	✓

*- some theory; ** - Restricted to VARX

Table 1 – Univariate Models: Estimation of Stickiness

	Shampoo Brand SA				*Shampoo Brand SB*			
	Awareness	Consideration	Liking	Volume	Awareness	Consideration	Liking	Volume
Constant	0.378***	0.217***	2.957***	2.706	0.381***	0.453***	7.681***	4.271***
AR(1)	0.435***	0.218**	0.318***	0.321***	0.048	0.019	-0.109	0.326***
AR(2)	0.073	0.355***	0.153	0.292***	0.279***	-0.017	-0.154	0.149
AR(3)	0.287***	0.257***	0.355***	0.345***	0.320***	0.027*	-0.187	-0.037
R-square	0.480	0.451	0.443	0.758	0.245	0.020	0.060	0.156
Q(12) Statistic	7.198	11.640	10.814	7.479	9.787	13.022	6.513	14.953
Stickiness	0.722	0.830	0.673	0.958	0.599	0.027	0.000	0.326

	Bottled Water Brand WA				*Bottled Water Brand WB*			
	Awareness	Consideration	Liking	Volume	Awareness	Consideration	Liking	Volume
Constant	0.600***	0.470***	4.052***	131.183***	0.215***	0.834***	21.746***	351.486***
AR(1)	0.333***	0.225***	0.363***	0.610***	0.331***	0.303***	0.090	0.905***
AR(2)	0.238**	0.347***	0.119	0.161	0.081	0.366***	-0.064	0.135
AR(3)	-0.039	0.163	0.113	0.048	0.329***	0.081	-0.025	-0.121
R-square	0.225	0.346	0.249	0.586	0.393	0.440	0.104	0.863
Q(12) Statistic	11.344	9.504	8.443	0.819	9.867	17.940	10.970	10.310
Stickiness	0.571	0.572	0.363	0.610	0.660	0.669	0.000	0.905

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 2 – Attitude Response Models

	Shampoo Brand SA			*Shampoo Brand SB*		
	Awareness	Consideration	Liking	Awareness	Consideration	Liking
Constant	-0.701	-1.378**	0.014	-0.643***	-0.651***	2.344***
Price	-0.024	0.178	0.319	-0.502***	-0.128	-0.389
Promotion	0.023	0.052***	0.053***	0.054	0.006	0.083
Advertising	0.023***	0.006	0.003	0.007***	-0.001	-0.001
Carryover	0.436***	0.400***	0.386***	0.029	0.030	-0.106
R-square	0.533	0.363	0.410	0.200	0.011	0.040
Q(12) Statistic	17.939	17.550	14.140	19.782	11.031	14.128

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

	Bottled Water Brand WA			*Bottled Water Brand WB*		
	Awareness	Consideration	Liking	Awareness	Consideration	Liking
Constant	-1.174***	-2.827***	-0.789*	-0.322	-0.116***	2.948***
Price	-0.598*	-1.915***	-1.643***	0.037	0.006	0.069
Promotion	0.047	0.033*	0.045	0.028	0.044	-0.023
Advertising	0.014***	0.003	0.000	0.019***	0.003	0.007
Carryover	0.362***	0.082	0.226**	0.593***	0.622***	0.230**
R-square	0.410	0.433	0.347	0.559	0.440	0.073
Q(12) Statistic	23.383	10.442	7.644	23.699	24.741	11.880

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 3 – Sales Response Models

	Shampoo Brand SA	*Shampoo Brand SB*
Constant	0.012	1.193***
Price	-0.080	-0.466***
Promotion	0.083***	0.076
Advertising	0.005	0.001
Carryover	0.733***	0.310***
R-square	0.752	0.218
Q(12) Statistic	17.252	17.814

	Bottled Water Brand WA	*Bottled Water Brand WB*
Constant	1.083***	5.680***
Price	-0.937***	-0.084
Promotion	0.055***	0.008
Advertising	0.005***	-0.002
Carryover	0.538***	0.922***
R-square	0.696	0.862
Q(12) Statistic	6.388	7.223

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 4 – Sales Conversion Models

	Shampoo	*Bottled Water*
Constant	-1.665***	0.181
Awareness	0.251***	0.050*
Consideration	0.169***	-0.065
Liking	0.462**	0.517**
Carryover	0.552*	0.786***
R-square	0.820	0.975

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 5: Predictive Performance for
Marketing Mix Model vs. Consumer Attitude and Marketing Mix Model

Holdout sample: periods 85 through 96

Forecast Solution	**Category**	**Brands**	**Marketing Mix**	**Consumer Attitude + Marketing Mix**	**Improvement**
			MAPE	MAPE	
One-step ahead	Water	WA	6.2%	3.7%	40%
		WB	0.9%	0.5%	41%
		WC	9.4%	12.6%	-33%
		WD	7.0%	6.0%	14%
	Shampoo	SA	5.5%	2.1%	61%
		SB	1.0%	0.6%	39%
		SC	5.3%	0.4%	93%
		SD	2.4%	3.5%	-50%
		SE	0.9%	0.7%	22%
		SF	8.5%	8.5%	1%
Multi-step	Water	WA	12.0%	6.2%	48%
		WB	7.2%	4.4%	39%
		WC	24.6%	22.2%	10%
		WD	14.5%	10.7%	26%
	Shampoo	SA	8.6%	2.1%	76%
		SB	1.6%	1.0%	36%
		SC	6.8%	0.4%	94%
		SD	5.4%	7.4%	-37%
		SE	1.2%	0.8%	37%
		SF	12.2%	12.0%	2%

Note: MAPE denotes the Mean Absolute Percent Error over the 12-month forecast period. One-step ahead forecasts update each consecutive period, while multi-step forecasts predict one to twelve-periods-ahead predictions without updating.

Table 6a

Advertising and Promotion Scenarios – Shampoo Brand

Panel A: Aggressive Advertising Scenario

	Start	New	Gain	LT Gain	Conversion			
Advertising	100	500	400					
Promotion	100	100	0					
Awareness*	0.270	0.278	3%	5%	1.2%	Long-term Sales Gain=		2.2%
Consideration	0.170	0.172	1%	2%	0.4%	Due to Mindset=		1.7%
Liking	5	5	0%	0%	0.1%	Due to Transactions=		0.6%
Sales	1.800	1.819	1%	2.2%				

*Read: initial awareness is 27%. Quintupling advertising spending (from index 100 to index 500), while keeping promotion the same, raises awareness to 27.8%, for a 3% gain. This gain translates into a 5% long-term gain, which converts to a 1.2% sales gain. Total sales gain is 2.2%, of which 1.7% (=1.2+0.4+0.1) is due to movements in attitudinal metrics.

Panel B: Aggressive Sales Promotion Scenario

	Start	New	Gain	LT Gain	Conversion			
Advertising	100	100	0					
Promotion	100	200	100					
Awareness	0.270	0.273	1%	2%	0.4%	Long-term Sales Gain=		16.8%
Consideration	0.170	0.176	3%	6%	1.2%	Due to Mindset=		2.3%
Liking	5	5.05	1%	1%	0.7%	Due to Transactions=		14.4%
Sales	1.800	1.942	8%	16.8%				

Table 6b

Advertising and Promotion Scenarios – Water Brand

Panel C: Aggressive Advertising Scenario

	Start	**New**	**Gain**	**LT Gain**	**Conversion**			
Advertising	100	500	400					
Promotion	100	100	0					
Awareness	0.36	0.366	2%	3%	0.3%	Long-term Sales Gain=		2.1%
Consideration	0.32	0.321	0%	0%	0.0%	Due to Mindset=		0.3%
Liking	6	6	0%	0%	0.0%	Due to Transactions=		1.8%
Sales	130.000	131.050	1%	2.1%				

Panel D: Aggressive Promotion Scenario

	Start	**New**	**Gain**	**LT Gain**	**Conversion**			
Advertising	100	100	0					
Promotion	100	200	100					
Awareness	0.36	0.368	2%	4%	0.3%	Long-term Sales Gain=		7.3%
Consideration	0.32	0.324	1%	2%	0.0%	Due to Mindset=		1.1%
Liking	6	6.06	1%	1%	0.8%	Due to Transactions=		6.1%
Sales	130.000	133.655	3%	7.3%				

Table 7: Strategic Importance of Attitudinal Metrics

Impact Potential	Sales Conversion	
	Low	**High**
Low	Transactions effect at best	Wrong marketing instrument
High	Wrong focus	Long-term effect potential