Dominique M. Hanssens & Koen H. Pauwels

Demonstrating the Value of Marketing

Marketing departments are under increased pressure to demonstrate their economic value to the firm. This challenge is exacerbated by the fact that marketing uses attitudinal (e.g., brand awareness), behavioral (e.g., brand loyalty), and financial (e.g., sales revenue) performance metrics, which do not correlate highly with each other. Thus, one metric could view marketing initiatives as successful, whereas another could interpret them as a waste of resources. The resulting ambiguity has several consequences for marketing practice. Among these are that the scope and objectives of marketing differ widely across organizations. There is confusion about the difference between marketing effectiveness and efficiency. Hard and soft metrics and offline and online metrics are typically not integrated. The two dominant tools for marketing impact assessment, response models and experiments, are rarely combined. Risk in marketing planning and execution receives little consideration, and analytic insights are not communicated effectively to drive decisions. The authors first examine how these factors affect both research and practice. They then discuss how the use of marketing analytics can improve marketing decision making at different levels of the organization. The authors identify gaps in marketing's knowledge base that set the stage for further research and enhanced practice in demonstrating marketing's value.

Keywords: accountability, marketing effectiveness, efficiency, return on marketing investment, marketing value assessment

The Difficulty of Marketing Value Assessment

> I want marketing to be viewed as a profit center, not a cost center.
>
> —A chief executive officer
>
> I have more data than ever, less staff than ever, and more pressure to demonstrate marketing impact than ever.
>
> —A chief marketing officer

Marketing is at a crossroads. Managers are frustrated by the gap between the promise and the practice of effect measurement, big data, and online/offline integration. Caught between financial accountability and creative flexibility, most chief marketing officers (CMOs) do not last long at their companies (Nath and Mahajan 2011). Top management has woken up to the fact that their companies make multimillion-dollar marketing decisions on the basis of less data and analytics than they devote to thousand-dollar operational changes. Customer and market data management, product innovation and launch, international budget allocation, online search optimization, and the integration of social and traditional media are just some of the profitable growth drivers that greatly benefit from analytical insights and data-driven action. Yet marketing value assessment, defined as the identification and measurement of how marketing influences business performance as well as the accurate calculation of return on marketing investment (ROMI), remains an elusive goal for most companies, which are struggling to integrate big and small data and marketing analytics into their marketing decision and operations.

Why is marketing value assessment so challenging? To begin with, the term "marketing" refers to several things: a management philosophy (customer centricity), an organizational function (the marketing department), and a set of specific activities or programs (the marketing mix). However, regardless of the intended use of the term, marketing aims to create and stimulate favorable customer attitudes with the goal of ultimately boosting customer demand. This demand, in turn, generates sales and profits for the brand or firm, which can enhance its market position and financial value. This sequence of influences has been termed the "chain of marketing productivity" (Rust et al. 2004), as depicted in Figure 1.

As a result, marketing has multiple facets, some attitudinal, some behavioral, and some financial. However, the relation between the metrics that assess these facets is complex and nonlinear (Gupta and Zeithaml 2006), and their average correlations are below .5 (Katsikeas et al. 2016). For example, product differentiation tends to be associated with higher customer profitability but lower acquisition and retention rates (Stahl et al. 2012). Similarly, online behavior and offline surveys yield different information to explain and predict brand sales (Pauwels and Van Ewijk 2013). Likewise, some attitudinal brand metrics (esteem, relevance, and knowledge) are associated with higher sales but not with higher prices, while others (energized differentiation) show the opposite pattern (Ailawadi and Van Heerde 2015).

This makes it difficult for researchers to synthesize findings across studies of marketing impact, and it makes it difficult for organizations to choose which metrics to rely on

Dominique M. Hanssens is Distinguished Research Professor of Marketing, Anderson School of Management, University of California, Los Angeles (e-mail: dominique.hanssens@anderson.ucla.edu). Koen H. Pauwels is Professor of Marketing, Özyeğin University (e-mail: koen.pauwels@ozyegin.edu.tr).

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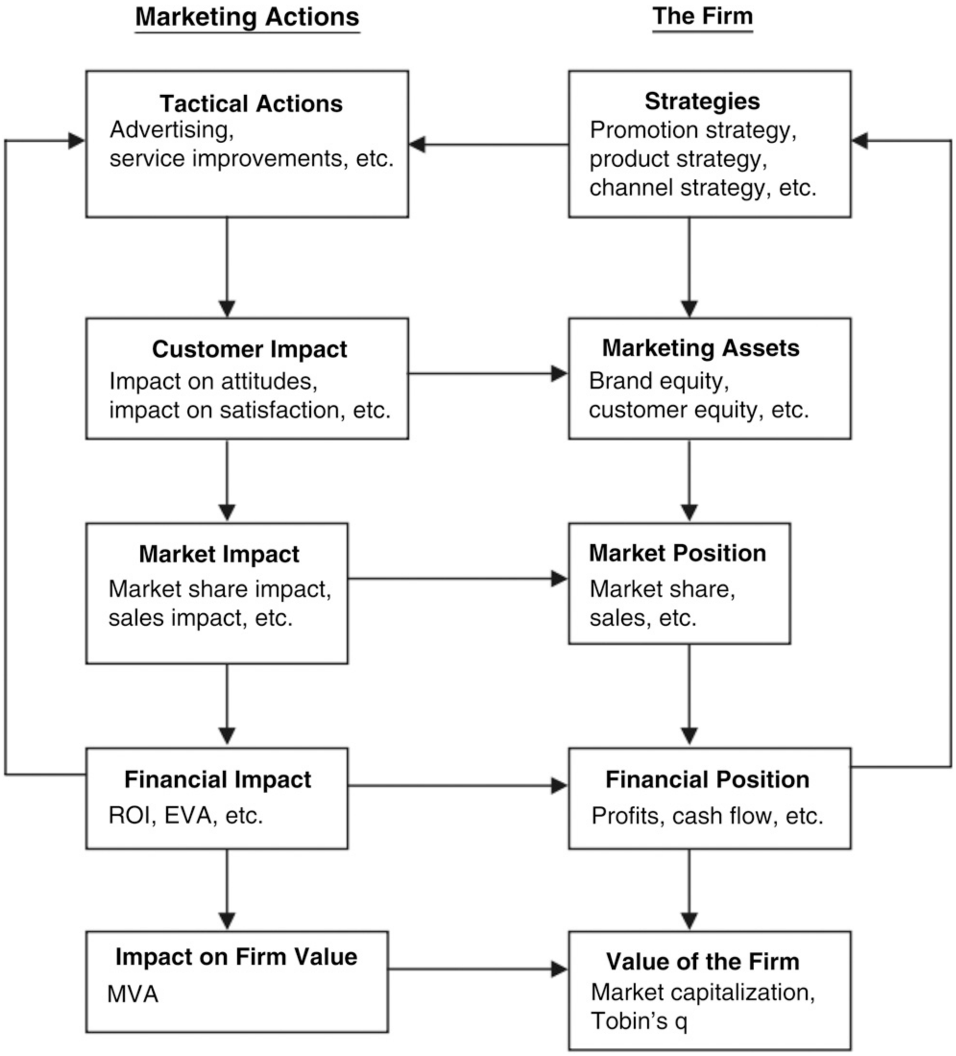
FIGURE 1
The Chain of Marketing Productivity



Source: Rust et al. (2004).
Notes: EVA = economic value analysis; MVA = marketing value analysis.

when making resource allocation decisions. For example, advertising is only deemed financially successful if its ability to increase awareness results in higher sales and/or profit margins.

Current efforts in marketing measurement often do not go all the way in connecting metrics to each other. For instance, many balanced scoreboards and dashboards do not tell managers how their marketing inputs relate to customer insight metrics and to product market performance metrics. Consistent with this notion, in a personal communication, Lehmann uses the term "flow-boards" for dashboards connecting metrics, while Pauwels (2014) defines analytic dashboards as a concise set of interconnected metrics. Indeed, reconciling multiple perspectives on marketing value requires causality to be shown among marketing actions and multiple performance outcomes (e.g., customer attitudes, product markets, financial markets; i.e., quantifying the arrows in Figure 1). Connecting the metrics is especially challenging if data and decisions exist in silos within the organization. However, the consumer or customer is the target and recipient of *all* these actions, the combination of which will create the consumer's attitude toward the brand and, eventually, his or her purchase behavior. In assessing marketing's value, we therefore pay close attention to the *integration* of marketing activities as they affect consumer behavior. In this context, Court et al. (2009) argue that the critical task is to describe the process that generates sales for the firm and to identify the bottlenecks that impede profitable business growth.

In addition to relating performance metrics to each other (the metrics challenge), these metrics also need to be connected to marketing activity. Indeed, assessing marketing value requires various demand functions that quantify how changes in marketing activity influence changes in these dependent variables (e.g., with response elasticities). Demand functions are often too complex for senior managers to intuitively understand and estimate. Consequently, marketing analytics expertise is needed, either in-house or through specialized suppliers, which in turn creates an organizational challenge because those who practice marketing tend to be different from those who measure it. A final necessity in marketing value assessment is effective communication within the organization, including to decision makers who may not be fluent in the technical aspects of value measurement.

Despite the challenges, the benefits of "marketing smarter" are substantial, as both academic studies and business cases demonstrate. Even a small improvement in using marketing analytics creates, on average, 8% higher return on assets to the companies, compared with their peers (Germann, Lilien, and Rangaswamy 2013). This benefit increases to 21% for firms in highly competitive industries. Organizations of any size and in any industry have had a sustainable competitive advantage from using marketing analytics. However, even the large U.S. companies that participated in the CMO Survey (2016) report that marketing analytics are used in only 35% of all marketing decisions. This percentage is expectedly even lower for small and medium-sized firms across the world.

The causality implied by the chain of marketing productivity increases the pressure for good performance metrics, causal links between metrics and marketing actions, and effective communication to demonstrate the value of a firm's marketing. This article discusses the challenges of obtaining those three things. We first provide a general overview, critically examining the knowledge base and practice of marketing value assessment in organizations. We then discuss marketing objectives and how they determine the choice of marketing metrics. Next, we turn our attention to the research methods that drive marketing value assessment—namely, the use of models, surveys, and experiments. Those methods have generated several important findings about marketing value. Then, because marketing analysts and marketing decision makers are typically not the same people, we examine ways of improving how marketing value is communicated within the organization. We conclude with a brief summary of current knowledge and important areas for further research.

The Influence of Marketing Objectives on Marketing Value Metrics

As organizations grow and marketing technologies evolve, marketing tasks become increasingly specialized and complex. A vice president for sales and marketing may be replaced by two vice presidents, one for sales and another for marketing. Within marketing, separate departments may focus on advertising and customer service. Advertising itself may be divided into brand and direct, offline and online. Each of these people or departments is held accountable for increasingly focused business objectives and performance metrics. In customer service, the performance measure may be the Net Promoter Score, while brand recognition scores may be used to gauge the performance of the brand advertising team, and CPM (cost per 1,000 prospects touched) may be used for the direct advertising team.

The result is an increasingly siloed marketing department in which each specialized function has its own objectives, with little consistency across functions. Another consequence may be the imposition of inappropriate efficiency metrics that make marketing less impactful. In some cases, marketing may be treated as an expense rather than an investment. What is needed are guidelines for (1) reconciling different marketing objectives, (2) distinguishing between marketing effectiveness and efficiency, (3) defining the scope of marketing, and (4) distinguishing between marketing budget setting and budget allocation.

Reconciling Different Objectives for Marketing

Among the multitude of objectives marketing managers aim to achieve are gains in sales volume and growth, market share, profits, market penetration, brand equity, stock price, and a variety of consumer mindset metrics, such as awareness and consideration. Table 1 presents an overview of the focus of different performance assessments, their benefits, and their drawbacks.

Marketing scholars can no longer assume that profit maximization is the sole goal of marketing (see Keeney and Raiffa 1993). When Natter et al. (2007) optimized dynamic pricing and promotion planning for a retailing company, having initially agreed to maximize profits, their recommendation of higher prices met with substantial resistance from the purchasing managers, whose supplier discounts depend on sales volume, and from local branch managers, who insisted on keeping a market leadership position in their city. After further discussion, they decided to combine profits, total sales volume, and local market share objectives in an overall goal function for the model to optimize. The resulting model yielded recommendations that were more acceptable to the managers, who successfully implemented them.

Despite individual contributions such as Natter et al. (2007), marketing academia and practice have not produced a set of generalizable weights for using different objectives under different conditions. Instead, marketing practice tends to focus on case studies of each company's unique situation and, within the firm, on individual executives' siloed departments.

Further research should attempt to bridge marketing objectives and metrics across functional, geographical, and life cycle boundaries. Bronnenberg, Mahajan, and Vanhonacker (2000) provide a good example: they demonstrate that, in one product category, consumer liking and distribution are dominant success metrics for brands in the early phases of the category life cycle, with pricing and advertising becoming important only later. Similarly, Pauwels, Erguncu, and Yildirim (2013) show that brand liking matters more in mature markets, but brand consideration is more important in emerging markets. Research should also investigate the optimal weighting of objectives on the basis of hard performance measures, along the lines of research that combines model-based and managerial judgment (Blattberg and Hoch 1990). Recently, the notion that models should not ignore human decision makers has reemerged within a big-data context as algorithmic accountability (Dwoskin 2014). The goal is to tweak social media classification algorithms not for maximum efficiency but to avoid human-relations mistakes (Lohr 2015). A widely shared example is that of Target, which sent out pregnancy-related coupons to teenagers for whom its algorithm

TABLE 1
Types of Performance Outcomes

Aspect of Performance	Advantages	Disadvantages	Considerations
Customer mindset	• Causally close (often closest) to marketing actions • May be unique to marketing performance outcomes vs. other business disciplines • Commonly used to set marketing-specific goals and assess marketing performance in practice	• Primary data may be difficult and costly to collect if direct from customers • Secondary data from research vendors may not align well with theorized constructs or data from other vendors	• Sampling: current customers versus past customers versus all potential customers in the marketplace • Possible demographic effects on measures • Noise in survey measures (primary and secondary data) • Only allows for goal-based assessment if collected with or supplemented by primary data • Transaction-specific versus overall evaluations
Customer behaviors	• Causally close to marketing actions • May be unique to marketing performance outcomes versus other business disciplines • Commonly used to set marketing-specific goals and assess performance in practice • Direct observation shows revealed preferences	• Primary data may be difficult and costly to collect if direct self-reports from customers • Observed behavior data may require working with firms and can be difficult to collect from multiple firms • Differences across firms in how observed behaviors are defined and calibrated	• Noise in survey measures (primary data) • Only allows for goal-based assessment if collected or supplemented by primary data
Customer-level outcomes	• Causally close to marketing actions • May be unique to marketing performance outcomes versus other business disciplines • Commonly used to set marketing-specific goals and assess performance in practice	• May require working directly with firms and may be difficult to work with multiple firms • Differences across firms in how economic outcomes are determined and calculated	• Only allows for goal-based assessment if collected or supplemented by primary data • Noise in survey measures (primary data)
Product-market-level outcomes	• Causally close to marketing actions • May be unique to marketing performance outcomes versus other business disciplines • Commonly used to set marketing-specific goals and assess performance in practice	• Unit sales data are difficult to obtain from secondary sources for most industries • Even firms in the same industry may differently define the markets in which they compete • Higher level of aggregation, so may be less diagnostic	• How to define the "market" • Only allows for goal-based assessment if collected or supplemented by primary data • Noise in survey measures (primary data)
Accounting	• Well-defined and standardized measures • Revenue-related items commonly used to set marketing-specific goals and assess marketing performance in practice • Secondary data availability • For primary survey data, specific items likely to have the same meaning across firms	• Corporate level, so may be further away from marketing actions and less diagnostic • Not forward looking • May undervalue intangible assets • Mostly ignores risk • Treats most marketing expenditures as an expense	• Potential differences between firms and industries in their accounting practices, policies, and norms • Differences in measures across countries • Only allows for goal-based assessment if collected or supplemented by primary data • Noise in survey measures (primary data)
Financial market	• Investors (and analysts) are forward looking • May better value intangible assets • Finance theory suggests that investors may be more goal agnostic (but time frames and even criteria may be goal related from the firm's perspective) • Secondary data availability	• Corporate level, so may be further away from marketing actions and less diagnostic • Publicly traded firms only, which tend to be larger • Difficulties in assessing firms across different countries (and financial markets) • May be subject to short-term fluctuations unconnected with a firm's underlying performance	• Risk adjustment • Public/larger firm sample-selection bias • Assumes primacy of shareholders among stakeholders, but this may not be true in some countries • Assumes the financial market is efficient and participants are well informed of the marketing phenomena being studied • Only allows for goal-based assessment if collected or supplemented with primary data • Noise in survey measures (primary data)

Source: Katsikeas et al. (2016).

predicted pregnancy (Hill 2012). Marketing is in a unique position to contribute to the debate on the use of such algorithmic predictions by applying the rich existing literature on quantifying the consequences of loss in customer goodwill and estimating the probabilities of these loss scenarios.

Effectiveness and Efficiency

When we understand the target objectives of decision makers, a key question is whether they give primacy to effectiveness or efficiency in reaching these goals. Effectiveness refers to the ability to reach the goal; efficiency refers to the ability to do so with the lowest resource usage. For instance, mass media advertising may be effective in reaching the vast majority of prospective customers, but it is not very efficient, whereas online advertising may be very efficient but not as effective because it reaches fewer prospective customers.

The value of marketing can be expressed in terms of either effectiveness or efficiency. Return on marketing investment deals with efficiency. When efficiency is the goal, the result is almost always a budget reduction through the elimination of the least efficient marketing programs. However, the firm may be more interested in the effectiveness of a marketing action, which may be better expressed as return minus investment, without dividing by the investment as in the standard return on investment (ROI) formula from finance. As an illustration, consider two mutually exclusive projects (e.g., alternative ad messages aimed at the same segment), with returns of $100 million and $10 million, respectively, and investment costs of $80 million and $2 million at the same level of risk. The first project has the larger net return ($20 million is greater than $8 million), but the second project has the larger ROI (25% is less than 400%). Which project should a manager prefer?

The trade-off between effectiveness and efficiency is particularly salient when there is a conflict between short-term and longer-term goals. Price promotional tactics, for example, may be optimized for their short-term profitability, but the repeated use of such tactics is known to erode brand equity over a longer time span (Mela, Gupta, and Lehmann 1997). Efficiency-driven marketing decisions should be supported only when they do not jeopardize the long-term viability of the brand.

Ultimately, firms want to strike a balance between effectiveness and efficiency goals. To accomplish this, beverage company Diageo displays marketing actions on a 2 × 2 matrix that juxtaposes their effectiveness (on defined objectives) with their efficiency (ROMI). Actions without sufficient effectiveness are likely to be canceled, no matter how high their ROMI, while effective but inefficient actions are reexamined to improve efficiency in the future (Pauwels and Reibstein 2010). A company may benefit from instituting a threshold return value that marketing programs must achieve to be supported. Examples of such thresholds are the firm's cost of capital and its economic profit (Biesdorf, Court, and Willmott 2013). Research is needed to establish what the thresholds for impact and efficiency should be.

Beyond defining and relating multiple objectives, we also need to conceptually and empirically relate effectiveness and efficiency in reaching these objectives. Measuring the effectiveness or the efficiency of marketing is not an easy task. It is important to measure not only the percentage return of any spending amount but also its magnitude. Conceptual and empirical models of marketing effectiveness show diminishing returns (e.g., Kireyev, Pauwels, and Gupta 2016; Little 1979), implying that ROI (efficiency) is maximized at levels of marketing spending that are below profit maximizing (effectiveness) (Pauwels and Reibstein 2010). We propose that the goal should be to maximize the total effectiveness when a certain threshold is achieved, even if that reduces the overall efficiency (Farris et al. 2015). However, our proposal may be more applicable to large organizations, which have plenty of resources and opportunities, than to small ones. Further research is needed to determine the best mix of effectiveness and efficiency for smaller organizations and in dire times.

The Scope of Marketing Within the Organization

The scope of marketing is one of the key determinants of its objectives and of the effectiveness/efficiency decisions that the marketing department makes (e.g., Webster, Malter, and Ganesan 2003). In some organizations, the marketing department is only responsible for a subset of the marketing mix, such as executing advertising campaigns and running sales promotions. Marketing decision makers are typically more junior in such organizations. Pricing, distribution, and product decisions are made elsewhere in the organization, by more senior decision makers. In our experience, this situation is typical in emerging countries, in engineering-dominated companies, and in business-to-business industries.

At the other extreme, a few organizations consider the marketing department to be the true profitable growth driver and both hold it accountable for profitable growth and provide it with the necessary resources and authority to achieve it. Examples include Procter & Gamble and Diageo, which are marketing-dominated companies in business-to-consumer industries (Pauwels 2014). Most companies fall somewhere between these extremes; they may hold marketing responsible for pricing, promotion, and branding, but not for creating successful new products (which is often the domain of research and development or a new product development group) or expanding distribution (which is often the domain of the sales organization).

The scope of marketing also has a major impact on the data collection that underlies marketing value assessment. The broader the scope, the more variables are included in marketing databases and, generally, the lower the level of granularity of these databases. For example, digital attribution models have a very narrow scope (determining which combination and sequencing of digital media impressions produces the highest consumer response) but can be executed daily or even hourly (see, e.g., Li and Kannan 2014). In contrast, complete marketing-mix models that include product innovation and sales call metrics in addition to various marketing communication and sales promotion variables are typically executed monthly or weekly. The latter, however, assign a much broader responsibility to marketing than do the former. At the same time, greater data granularity necessitates more advanced econometrics. A detailed discussion of econometric advances in market response modeling is beyond the scope of this article and may be found in Hanssens (2014).

How has academic research advanced the understanding of the importance of marketing scope? Far too little, argue Lee, Kozlenkova, and Palmatier (2015). In a recent review, they call for structural marketing: explicit consideration of organizational structure when assessing the value of marketing. They hypothesize that moving to a customer-facing structure increases effectiveness but reduces efficiency in obtaining data on how products perform. A few academic articles have investigated whether a more customer-focused organizational structure induces a market orientation, with mixed findings. Likewise, the 2015 Marketing Science Institute conference on "Frontiers in Marketing" featured several management questions and comments on the cost–benefit trade-offs of customer-focused teams.

Our recommendation is twofold: we agree with Lee, Kozlenkova, and Palmatier's (2015) call for more research on the impact of organizational structure on market-related outcomes, but we would also like to see more attention paid to the relationship between marketing performance and marketing scope. To what extent does excellent performance help marketing increase its scope and get it a "seat at the table" (Webster, Malter, and Ganesan 2003)? Or is it the communication of such performance (i.e., "marketing the marketing department") that matters most? Because the answer may depend on the industry and company setting, we recommend further research on the boundary conditions of the interplay between organizational structure, marketing actions, and performance outcomes.

Marketing Decisions: Budgets or Allocations?

It is important to know whether marketing actions are considered tactical or strategic in assessing their value. Broadly speaking, managerial decisions are either budget (investment) or allocation (execution) decisions (Mantrala, Sinha, and Zoltners 1992). For example, a CMO receives a $100 million budget from his or her CEO, for whom this $100 million represents an investment. The CMO allocates this budget to traditional media, digital media, and sponsorships. The owners of these three marketing groups make subsequent allocation decisions for their respective (smaller) budgets, and so on. Setting aside prevailing accounting standards that generally force these allocations to be expensed in the spending period, any marketing investment decision becomes an allocation decision one level down in the hierarchy.

The deeper in the organizational hierarchy one goes, the more tactical the allocation decisions become, and the more junior the decision makers are. For example, the decision to advertise on channel 4 rather than channel 7 is tactical relative to the higher-order decision to allocate 40% of the marketing budget to television advertising. At the same time, the deeper one goes in the hierarchy, the more detailed the available databases are and, therefore, the more opportunity for analytics-enhanced decision making. Such tactical decisions lend themselves to continuous data collection and decision automation, which is a decentralizing force in the organization (Bloom et al. 2014). However, analytics and decision support systems should support the different decision-making modes of optimizing (typical for very structured, tactical marketing problems), reasoning, analogizing, and creating (typical for more strategic marketing problems) (Wierenga and Van Bruggen 2012).

Academic research in marketing has tended to focus on tactical decisions rather than on strategy. For example, product line and distribution elasticities are at least seven times higher than advertising elasticities, which makes them strategically more relevant (Ataman, Van Heerde, and Mela 2010; Shah, Kumar, and Zhao 2015), but the abundance of data on the latter has resulted in many more academic publications on advertising effects than on distribution or product line effects on business performance. This tendency is amplified by the increased availability of micro-level marketing data, especially in digital marketing.

Academic research specifically on strategy versus tactics has focused mainly on the relative merits of setting the budget size or allocating a given budget (e.g., Mantrala, Sinha, and Zoltners 1992). More recently, Holtrop et al. (2015) show that competitive reactions on a strategic level differ substantially from reactions at a tactical level. Interestingly, strategic actions (presumably by senior managers) follow marketing theory expectations, whereas tactical actions (presumably by junior managers) often violate research recommendations by (1) retaliating when unwarranted and with an ineffective marketing instrument and (2) accommodating with an effective marketing instrument. Manchanda, Rossi, and Chintagunta (2004) obtain similar findings. Both articles focus on the pharmaceuticals industry; their important results regarding suboptimal marketing resource allocations are in need of replication in different sectors.

In marketing practice, the focus on marketing tactics benefits the organization's accountability and profitability but rarely creates sustained business growth, which is a more strategic objective. For business growth, product and process innovation become more important, as evidenced by empirical work demonstrating the positive impact of innovation on firm value (e.g., Sorescu and Spanjol 2008).

Analytics in the product innovation area has focused mainly on measuring consumer response to new product offerings—in particular, using conjoint analysis. The internal customer of such work is typically the product development group, which is a separate entity from marketing, with a separate budget. As a result, the insights from one function are rarely incorporated in the other; for example, the results from conjoint analyses (used by the product development group) are typically not included in marketing-mix models (used by the marketing group). The critical element of product appeal (e.g., conjoint utility) may therefore be missing from demand models, resulting in lower-quality sales forecasts.

A powerful illustration of the strategic importance of innovation is in investor reactions to new product launches, as measured by stock returns. Not only is investor reaction typically positive, despite the costs and the risk involved, but it occurs well ahead of the typical diffusion pattern of the new product. As an example, when Honda introduced the "sunken third-row seat" innovation in its minivan, the Odyssey, the innovation effect was fully absorbed in its stock price in approximately 12 weeks, whereas the sales diffusion of the product is much longer. One can surmise that investors realize the financial value of such an innovation after the first few weeks of positive consumer feedback and then assume that the marketing of the innovation will be well executed, so that the new product can reach its full market potential (Pauwels et al. 2004).

We recommend a broad definition of marketing in the organization and a commensurate broad inclusion of business functions in the generation of demand models for marketing resource allocation. This task can be complex because data from a variety of sources need to be combined in an integrated data and analytics platform. Importantly, such a platform can become the much-needed integrator of intelligence for senior management decisions and, as such, a centralizing force in the modern enterprise (Bloom et al. 2014). This means that the same strategic asset—the data and analytics platform—serves as both a centralizing (of intelligence) and a decentralizing (of execution) force, whereby both directions offer tangible advantages to the firm.

Methods and Findings About Assessing Marketing Value

Marketing value measurement has both a methodological and a knowledge component. We focus on these two here, leaving the third component, communication of marketing value, to the next section.

Methods: Models, Surveys, and Experiments

Marketing impact can be assessed empirically in two ways: by modeling historical data (secondary data) and by running surveys and experiments (primary data). Both methods have their proponents and advantages; however, neither is typically sufficient by itself to convince decision makers of the value of marketing and to induce change in marketing decision making.

The use of historical data sources has benefited tremendously from improvements in consumer and marketing databases and from developments in statistics (mainly econometrics) and computer science. On the data side, recent history has seen the emergence of scanner databases; customer relationship management databases; and digital search, social media, and mobile-marketing databases. On the modeling side, a steady stream of econometric and computer science advances has delivered the improvements in estimation methodology necessary to deal with these novel data (Hanssens 2014; Ilhan, Pauwels, and Kübler 2016; Murphy 2012).

Criticism of models estimated on historical data stems mainly from their limitations in capturing "reasons why" (as shown in surveys) or causal connections (as shown in experimental manipulations). A survey may show that one consumer visited the brand's website for reasons of purchase interest, whereas another visited to rationalize his or her choice for a competing brand—information not obtainable from models estimated on historical data.

In particular, the "two geneities" (heterogeneity and endogeneity) are challenging for marketing modelers. Heterogeneity (i.e., differences in response to marketing among consumers) has been addressed successfully thanks to simulated Bayes estimators (for a comprehensive review, see Rossi, Allenby, and McCulloch 2005). Endogeneity (i.e., the existence of decision rules in marketing that may bias the results of statistical response estimation) continues to pose major challenges, which are discussed in Rossi (2014). However, as marketing databases become more granular (monthly data intervals become weekly, daily, hourly, or even real time), the endogeneity challenge is easier to handle because the response models become more recursive in nature. In these higher-frequency databases, attention shifts to long-term impact measurement, in particular the testing for persistent effects, for which modern time-series techniques are readily available (see Hanssens, Parsons, and Schultz 2001; Leeflang et al. 2009).

Field experiments, by contrast, require customers and/or managers to react to an intervention at the time of data collection and allow for a direct comparison of treatment and control conditions, thereby removing concerns about endogeneity. Unfortunately, field experiments are often costly to conduct, limited to changing only one or a few decision variables at a time, and require trust in the organization that disappointing outcomes will not be held against the manager. For example, managers and salespeople often object to being part of the control group for a potentially impactful marketing action. Even online, where experiments are relatively easy to implement, companies often refuse to do so (Ariely 2010). Finally, marketing experiments are run for a limited amount of time and therefore are typically unable to detect long-term effects of a particular marketing action. Exceptions include longitudinal single-source field experiments (e.g., Lodish et al. 1995) and digital-marketing experiments in which, under the right circumstances, subjects can be tracked digitally after the experiment has concluded in order to infer long-term effects.

The best insights on marketing value will come from the combined use of secondary and primary data. Indeed, taken together, models, surveys, and experiments provide the benefits of highest decision impact at a moderate cost and risk. Yet what is the best sequence? In our experience, a field experiment on a strategic decision is perceived as too risky without a model or survey to justify the treatment proposal. For instance, furniture company Inofec (Wiesel, Arts, and Pauwels 2011) first had analysts run a response model based on historical data. After simulating potential scenarios based on the model output, management decided to double spending on one marketing channel (paid search) and to halve it on the other (direct mail). In the ensuing field experiment, the treatment condition earned 14 times the net profit earned by the control condition. Modeling the data of the field experiment revealed that paid search continued to yield high returns but that the reduced direct-mail budget began to break even. As a result, the company further experimented with increasing paid search but kept direct mail at its new level.

In situations in which both approaches are feasible, we recommend the sequence of model, experiment, model, experiment (MEME) to obtain the maximum impact of analytics-driven decision making. At the same time, surveys and other methods should be used to provide insight into the "why" and "how" of customer behavior. Further research should analyze whether the MEME sequence is the most productive across situations, consider other possible sequences, and establish boundary conditions. Regardless of

TABLE 2
A Comparison of Allocating and Investing Marketing Resources

	Allocating	Investing
Resources	Budget is received from senior management	Budget is created for junior management
Objectives	Efficiency, accountability of resource use	Stimulating profitable growth for the brand or firm
Use of analytics	Detailed analysis of (typically) one marketing-mix element	Integration across the marketing mix
Key challenges/risks	Exaggerated belief in the strategic importance of one's own silo	Large financial consequences
Examples	Media-mix allocations Dynamic pricing	Product portfolio decisions across international markets

the method used, a critical question for management is whether market conditions will have changed by the time the actual decision is made. The beliefs that change outpaces analytic insights and that past patterns do not apply to the future hinder the use of marketing analytics in many organizations.

Findings on Marketing Investments and Allocations

Previously, we discussed investments and allocations in terms of their relationship to strategy and tactics. Next, we discuss findings more broadly. Table 2 shows differences between allocation and investment decisions on several fronts. Managers and academics are keenly interested in decision rules for both, as is evident from the fact that this topic appears frequently among the biennial research priorities disseminated by the Marketing Science Institute.

Notably, most applications in marketing analytics (including analytics exploiting big data) focus on the deep dive for tactical allocations (see Table 2). Insofar as these contributions overemphasize areas in which good data are readily available, they run the risk of being bogged down in details and failing to see the forest for the trees. In contrast, when complete marketing-mix data are used along with econometric methods for inferring long-term impact, marketing analytics can also be very helpful for strategic investment decisions and for quantifying risk in such decisions (e.g., Leeflang et al. 2009).

In academic research, empirical generalizations on sales response functions provide valuable guidance for marketing spending (Hanssens 2015). Table 3 provides a quantitative overview, expressed as sales or market value elasticity estimates. These relate directly to marketing spending rules by virtue of the fact that, at optimality, a firm should allocate resources in proportion to its response elasticities (Dorfman and Steiner 1954). Table 3 also indicates the extent to which the marketing variable is an organic growth driver (i.e., its impact on sales is sustained rather than temporary). This is an important distinction because it identifies the strategic nature of marketing activities. Although price promotions and advertising for existing brands (which often consume the majority of marketing's budget and effort) are not major organic growth drivers of company performance, marketing assets (e.g., customer satisfaction, brand equity) and actions (e.g., distribution, innovation) have a strong impact on long-term company value. In an example from the French market, Ataman, Van Heerde, and Mela (2010) demonstrated across 70 brands in 25 consumer product categories that only breadth of distribution (.61) and length of product line (1.29) had strong long-term sales elasticities. By contrast, long-term elasticities of advertising (.12) and sales promotion (–.04) were small or negative.

At this point, generalizations—expressed as response elasticities—exist for many quantifiable marketing inputs,

TABLE 3
Response Elasticities Summaries

	Typical Elasticity	Range	Drivers (+)	Organic Growth Driver?
Advertising	.1	0 to .3	Product newness, durables	Minor
Sales calls	.35	.27 to .54	Early life cycle, European markets	Major
Distribution	>1	.6 to 1.7	Brand concentration, high-revenue categories, bulky items	Major
Price	–2.6	–2.5 to –5.4	Stockkeeping unit level versus brand level, sales versus market share, early life cycle, durables	Minor
Price promotion	–3.6	–2 to –12	Storables versus perishables	No
E-word of mouth	Positive	.24 (volume) .42 (valence)	Low trialability, private consumption, independent review sites, less competitive categories	Possibly
Innovation[a]	Positive	N.A.	Radical versus incremental innovations	Major
Brand and customer assets[a]	.33 (brand) .72 (customer)			Major

[a]On firm value.
Source: Hanssens (2015).
Notes: N.A. = not applicable.

along with expected ranges and distinctions between short-term and long-term effects on sales. It is also apparent that firms generally deviate from optimal (profit-maximizing) spending in the marketing mix (i.e., they either over- or underspend). However, because the spending objectives of a firm or brand at any point in time are typically not known to the researcher, this conclusion about apparent suboptimality in spending remains tentative. One important conclusion that can be drawn from Table 3 is that marketing communications (i.e., advertising and sales calls) have the lowest elasticities. Their relatively flat response curves imply that they are unlikely to be the sole drivers of major performance change. However, when combined with one or more of the other marketing-mix elements, their impact can be substantial. For example, a recent study of high-level digital cameras demonstrated that when a camera brand receives highly positive reviews, advertising can have positive trend-setting effects on brand sales (Hanssens, Wang, and Zhang 2016). During these fleeting windows of opportunity, the combination of high perceived product quality and advertising produces long-lasting impact that neither driver can achieve by itself. Such findings illustrate that the timing and sequencing of marketing initiatives can be determining factors of their impact.

Recent research has identified conditions in which the most value is generated, such as distribution in emerging countries (e.g., Pauwels, Erguncu, and Yildirim 2013), new product launch during recessions (e.g., Talay, Pauwels, and Seggie 2012), and owned (vs. paid online) media for lesser-known products and for services (Demirci et al. 2014). We call for further research on these and other influential market conditions.

Researchers should not only help companies identify their response functions but also derive *where* on the function companies' current spending lies. This enables firms to determine whether to allocate more or less to various marketing activities than in previous years. Mantrala et al. (2007) demonstrate this for the publishing industry. An alternative approach is to run marketing experiments to assess alternative levels of expenditure and different programs and their resulting impact. This was done, for example, by the U.S. Navy to determine optimal levels of recruiters and advertising support to reach its manpower goals (Morey and McCann 1980). More recently, the advent of the digital marketing era has allowed for a more extended use of experimental designs to make advertising more effective. This is achieved principally through an improved understanding of the consumer journey (i.e., What are prospects' individual propensities to buy and how can they be increased through various targeted marketing efforts?; see, e.g., Li and Kannan 2014).

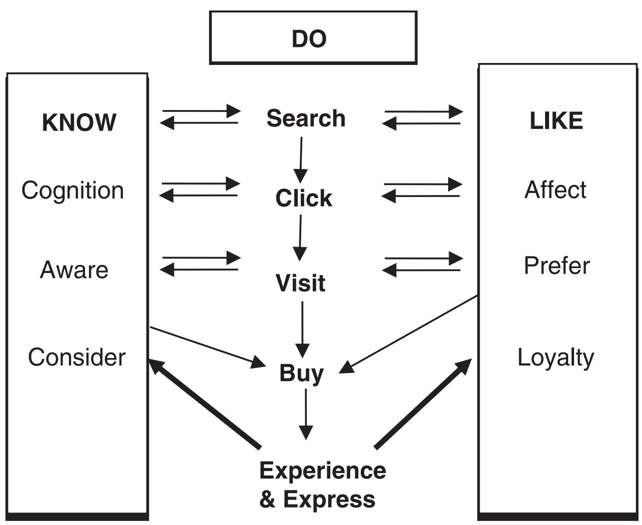
Connecting and Integrating Soft Metrics and Hard Metrics

Whereas finance practice is the domain of hard, monetary performance metrics, marketing practice has traditionally been the domain of soft, attitudinal metrics. The marketing literature has discussed attitude metrics at least since Colley's (1961) work on the effect of advertising on how targeted customers think and feel. Recent literature has demonstrated that including such attitude (or "purchase funnel") metrics in market response models increases their predictive and diagnostic power (Hanssens et al. 2014; Pauwels, Erguncu, and Yildirim 2013; Srinivasan, Vanhuele, and Pauwels 2010). Furthermore, the digital age has provided even more metrics of (prospective) customer behavior in customers' online decision journey (Court et al. 2009; Lecinski 2011). A key question is how to integrate soft (attitude) and hard (behavior) metrics, both conceptually and in empirical models (Marketing Science Institute 2014).

A recent study by Pauwels and Van Ewijk (2013) addresses this question both conceptually and empirically for 36 brands in 15 categories, including services, durables, and fast-moving consumer goods. They observe that survey-based attitude metrics typically move more slowly (i.e., have a lower variance) than weekly sales, while online behavior metrics move faster than weekly sales. Thus, attitudes and online actions represent, respectively, slow and fast lanes on the road to purchase. Dynamic system models reveal dual causality among survey-based attitudes and online actions, leading to the framework in Figure 2.

Although this road-to-purchase framework is inspired by the classical Think–Feel–Do distinction, it recognizes that the digital age provides many more metrics regarding customer behavior, including online search, clicks, website visits, and (social media) expressions of consumption and (dis)satisfaction. Online behavior does not simply reflect underlying attitudes (e.g., a known brand obtains higher click-through on its ads), it also shapes them. For instance, consumers shopping for their next smartphone may begin with a few brands in mind but then discover new ones online through reviews, (price) comparison sites, and social media, which increase their thoughts and feelings about those new brands (Court et al. 2009). This "zero moment of truth" (Lecinski 2011) of online

FIGURE 2
Integrative Model of Attitudes and Actions on the Consumer Road to Purchase



Source: Pauwels and Van Ewijk (2013).

discovery now precedes consumers' observing the brand at retail in the "first moment of truth" and consuming it in the "second moment of truth."

Only a few studies to date have quantified the connection between soft and hard metrics in ways that managers can use. Srinivasan, Vanhuele, and Pauwels (2010) analyze a large number of consumer products and report strong cumulative sales elasticities for advertising awareness (.29), consumer consideration (.37), and consumer liking (.59). A recent meta-analysis in digital marketing reveals that the sales elasticity of electronic word of mouth averages .42 for valence (sentiment) and .24 for volume (You, Vadakkepatt, and Joshi 2015). These elasticity results compare favorably with those in Table 3.

Although recent studies have provided some guidance on integrating soft metrics and online behavior into marketing analytics, more research is needed to learn the best ways to model the consumer decision journey and shed light on whether there are models that are more appropriate than the decision funnel (Marketing Science Institute 2014, p. 4). The findings are likely to be nuanced and to vary depending on the category (high involvement or low involvement) and existing brand strength (Demirci et al. 2014). This is an important agenda because attitudinal and transactional metrics are not highly correlated, and thus brands run the risk on focusing on the wrong performance metric in conducting their marketing valuations.

Dealing with Risk

Risk considerations have had little systematic coverage in marketing academia or practice. Studies of the relationship between marketing and firm value (the bottom box in Figure 1) have discussed risk factors because they are critical in investor valuation of assets or future income streams. Whereas the finance literature has focused mainly on systemic risk (i.e., risk faced by all companies in the market), the marketing literature offers insights into idiosyncratic risk (i.e., risk tied to unique circumstances of the specific company). For example, Rao and Bharadwaj (2008, 2016) demonstrate that effective marketing not only generates future cash flows but also lowers the working capital that is required to accommodate different scenarios in the economic environment. These authors argue convincingly that demonstrating the connection between marketing and firm value is essential if marketing is to be a part of strategic planning in the enterprise. An empowered CMO—defined as a proficient demand forecaster and marketing decision maker—is uniquely able to do this because of his or her "outside-in view" and knowledge about likely consumer response to different business initiatives. Drawing on that knowledge, the CMO can project cash flows and required working capital (both of which drive firm value) under different economic scenarios and then advise top management on the best course of action for the firm's shareholders. As such, marketing's ability to manage business risk is an integral part of its value creation for the firm.

In practical terms, an empowered CMO needs to showcase his or her ability to manage marketing-induced risk, given uncertainty about consumer, retailer, and competitive reactions and the timing of these responses (Pauwels 2014). Most studies that have examined the consequences of risk for marketing planning, execution, and results monitoring have performed scenario analyses that contrast best and worst cases on the basis of estimated standard errors of response coefficients. Only one academic article to date, by Albers (1998), has formalized this process. After specifying the response functions discussed in the previous section, Albers decomposes the deviation between actual and predicted performance as (1) incorrect market response assumptions (planning variance), (2) deviations of actual marketing actions from planned ones (execution variance), and (3) misanticipation of competitive reactions (reaction variance). Each of these variances can be decomposed further into the separate effects of single marketing instruments.

Planning variance. Incorrect market response assumptions can stem from faulty predictions of market size (driven by business cycle or other consumption trends that affect the entire sector) or market share (driven by brand-specific actions such as advertising messaging or relative price). Understanding the extent of deviation that results from each factor helps companies adjust future predictions and also assign accountability to the proper party (industry forecasters or brand managers). Although benchmarks exist for marketing effect size (see Table 3), the timing of marketing wear-in and wear-out effects remains uncertain in practice and is relatively underresearched.

While early research (Little 1970) has suggested the possibility of wear-in times for marketing campaigns, empirical evidence has mainly covered sales effects of advertising, new product introductions, and point-of-purchase actions. The peak sales effect of advertising occurs relatively quickly, typically within two months (Pauwels 2004; Tellis 2004), and the wear-in times for mindset metrics (e.g., awareness, liking, consideration) are just over two months (Srinivasan, Vanhuele, and Pauwels 2010). In contrast, new product introductions typically take several months or years to take off (Golder and Tellis 1997). As can be expected, point-of-purchase actions work either immediately or not at all (Pauwels 2004), with price promotions standing out as the most studied marketing action (Srinivasan et al. 2004). The effect of distribution changes seems to take longer (2.1 months on average in Srinivasan, Vanhuele, and Pauwels [2010]). Further investigation of distribution is important because distribution stands out as the most impactful marketing action (Ataman, Van Heerde, and Mela 2010; Bronnenberg, Mahajan, and Vanhonacker 2000). Finally, we know very little about the timing of ROIs in new (digital) media such as paid search, banner ads, and word-of-mouth referrals. Notable exceptions include DeHaan, Wiesel, and Pauwels's (2015) study of 11 online and 3 offline advertising forms for an online retailer and Trusov, Bucklin, and Pauwels's (2009) report that wear-out times are substantially higher for word-of-mouth referrals than for traditional marketing actions for a social networking site.

Similarly, we know little about the impact and temporal effects of marketing spending on brand and customer value, as opposed to sales response. In modeling terms, marketing brand value effects are generally captured by state-space models with

Kalman filters (e.g., Naik, Prasad, and Sethi 2008) or by Bayesian dynamic linear models (e.g., Ataman, Van Heerde, and Mela 2010). The idea is that insofar as marketing induces purchases that yield satisfactory consumer associations with the brand, future purchases may occur without marketing support, thus increasing baseline demand for the brand. Likewise, marketing actions may decrease price sensitivity and thus increase the price premium (Ataman et al. 2016). Other researchers have tracked the connection between marketing spending, customer acquisition, and the value these actions bring to the firm (Rust et al. 2004). Despite these methodological developments, we do not yet have a strong empirical knowledge base on how marketing creates brand and customer value over time.

Empirical generalizations on wear-in and wear-out effects are necessary for managerial advice in cases in which data are missing (Lehmann 2006). We need studies analyzing return timing for investments in new media and new (emerging) markets. Moreover, the timing of returns may systematically vary by medium and target audience, a possibility that should be taken into consideration when deciding on campaigns. Considerable research is still required to determine the contribution of marketing spending to a brand's value as well as when the firm realizes this value. Conversely, more research is needed on the impact of cessation or reduction of marketing, especially its long-term consequences. On that topic, Sloot, Fok, and Verhoef (2006) find that assortment reductions lower category sales in the short run, but less so in the long run. Although Li and Kannan (2014) find virtually no short-term sales loss from stopping paid search for a well-known brand, Kireyev, Pauwels, and Gupta (2016) show substantial long-term sales loss from reducing display and search ads for a lesser-known brand. Finally, Ailawadi, Lehmann, and Neslin (2001) report that Procter & Gamble's strategic decision to reduce price-promotional spending across 24 product categories resulted in a drop in long-term market shares but a gain in profitability. More research of this type will help the CMO project the impact of alternative marketing plans.

Execution variance and reaction variance. Execution variance is very important in practice but has had virtually no research in academia (Albers 1998). Marketing executions often stray from their plan because of third-party factors (e.g., the ad agency did not place billboards in time because local regulations and insufficient temporary employees) or for internal reasons, such as lower-level managers reacting more strongly to competitive moves than necessary (Holtrop et al. 2015). Albers (1998) provides the illustrative example of a product manager decreasing the price more than planned and switching the allocation away from distribution to advertising. Because such occurrences are widespread, execution variance and its consequences require further academic research.

In contrast, academic research on competitive reaction is plentiful, including research on its nature (aggressive, accommodating, or neutral), its speed, and its absence as a result of competitors' unawareness or inability to react (Chen 1996). Notably, managers often overestimate the incidence of competitive reaction (e.g., Holtrop et al. 2015) because research has shown that lack of reaction is the dominant response, at least for advertising and price promotions (Steenkamp et al. 2005). Even when there is a retaliatory competitive reaction, it typically decreases the sales benefit from price promotions across fast-moving consumer goods categories by only 10% (Pauwels 2007). Competitive response has a similarly small impact on the sales benefits of new product introductions, advertising, and distribution activity (Pauwels 2004). Further research is needed to determine the boundary condition of reaction size and variance. If competitive response variance is high, the firm may want to start a "competitive intelligence" initiative.

Beyond competitors, other market players (e.g., retailers) also influence the ROMI, as does the marketing organization itself—for example, through decision rules that favor repeating past successes (Dekimpe and Hanssens 1999). The marketing literature has focused thus far on estimating customer and competitor response to marketing actions, but much less so on the sector ecosystem response that includes other players and the company's own decision rules and heuristics (Dekimpe and Hanssens 1999). A few notable exceptions include studies on retailer pricing showing, for example, that retailers tend to increase a promoted price back to its regular level slowly rather than abruptly (Pauwels 2004; Srinivasan et al. 2004; Tsiros and Hardesty 2010). Company decision rules/heuristics include the managerial tendency to weigh past prices when setting future prices (Krishna, Mela, and Urbany 2000). Managers should be aware of such tendencies in their company's decision making and investigate whether it is appropriate to continue such habits in the current market environment.

The reaction of market players in offline environments has been assessed by dynamic system modeling in data-rich environments (e.g., Pauwels 2004) and by role playing in data-scarce environments, such as one-shot negotiations (Armstrong 2001). Further research is needed on the role of market player reactions in worldwide competition in online environments. As for research on the marketing–finance interface, more insights are needed to assess whether investors react appropriately to marketing actions and, thus, how valuable information about investor reaction is for marketing decision making.

A key research priority is to go beyond documenting reactions toward understanding the impact of that reaction on the ROI of the initiating action. For marketing-mix actions, is it really the case that the majority of the net sales impact derives *not* from customer reaction but from support from other marketing actions (Pauwels 2004)? For strategic marketing actions, how does one assess likely competitive reaction in deciding on location, product quality, and regular price level?

In conclusion, when marketing plans do not materialize as anticipated, the reasons can be various, as formalized by Albers (1998). Only when an organization can identify the reasons that apply to its own history can it take the right corrective actions. Risk analysis in marketing planning is more important to organizations than the paucity of prior research suggests and, as such, it is one of the most promising areas for further research. This is especially important if marketing is to become an integral part of strategic and financial planning.

Communicating Marketing Value Within the Organization

After defining and measuring marketing value, it is important to properly communicate this value within the organization. This creates closed-loop learning (see the feedback loops in Figure 1), which both justifies future marketing activities and examines them for increased effectiveness and/or efficiency. Internally communicating the value of marketing requires (1) communicating multiple objectives in marketing dashboards, (2) adapting communication to the style of the decision maker, and (3) adapting communication to the marketing organization.

Communicating Multiple Objectives in Marketing Dashboards

In addition to their stated objectives, decision makers also have personal objectives such as retaining their jobs and growing their career prospects. The use of marketing analytics is often impeded by a perception that analytics compete with people in the organization. Some managers may be fearful that the spread of analytics in decision making will eventually make them redundant in the organization. This need not be the case, as people and data (including models) have distinct competencies and weaknesses (e.g., Blattberg and Hoch 1990), which we summarize in Table 4.

Managers tend to excel at diagnosing new situations on the basis of their experience and integrating a variety of cues, especially so-called "broken-leg cues" (unusual situations that may not have prior history but are intuitively known to be important). However, human decision makers are also subjective in their judgment and tend to rush to a decision overconfidently, without properly accounting for uncertainty and risk. These weaknesses are well addressed by models, which account for uncertainty and weigh different cues on the basis of past data and "optimal" rules. However, the rules may be too rigid for a new situation, and the output of a model inevitably depends on human inputs, which the model is not designed to question.

Given those strengths and weaknesses, organizations should design decision support systems that take advantage of the distinctive competencies of managers while using technology to compensate for managers' inherent weaknesses. For example, after a firm's business goals for the next quarter or year are set, marketing planning should start with analytics or dashboard input. Then, decision makers need to judge the extent to which unique circumstances require some of the model outputs to be adjusted. Cross-functional input is paramount in this exercise, and there needs to be a sense of internal ownership of the analytics platform across the business functions. Finally, business objectives need to be tied to resource allocations. Corstjens and Merrihue (2003) give the example of global marketing resource allocation at Samsung: when a model-inspired reduction in marketing budget for product category Z in country X was enacted, the sales quota for the manager in charge of ZX was lowered as well, and vice versa for marketing spending increases. Such coordinated actions help create a culture in which managers view models and dashboards as their friends, not their nemeses. Automation of marketing decisions is likely to increase for tactical decisions in stable markets, but less so for strategic decisions, such as choosing new organic growth options, setting the rules for automation, and reacting to unexpected changes in turbulent markets (Bucklin, Lehmann, and Little 1998).

TABLE 4
Advice for Communication in Analytic and Intuitive Companies

Analytic Decision Making	Intuitive Decision Making
Present estimates	Visualize effectiveness
Discuss assumptions	Focus on main insights
Optimize allocation	Adjust allocation
Optimize budget	Adjust budget
Examples: Procter & Gamble, Allstate	Examples: Campbell's, Inofec

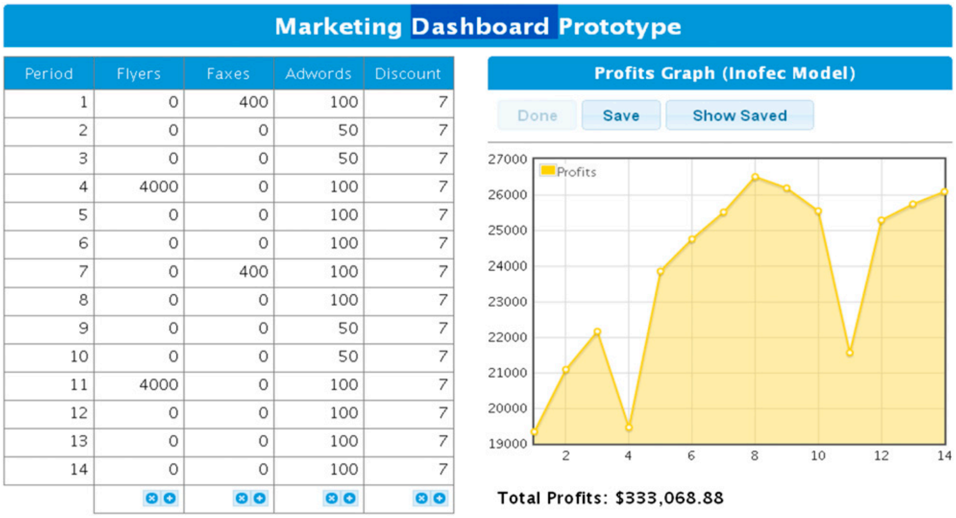
To combine the best of model-based and human-based strengths, researchers have proposed the use of an analytic marketing dashboard (Pauwels et al. 2009). Like the dashboard of a car, a marketing analytics dashboard brings the main multiple objectives and their metrics into a single display. It provides "a concise set of interconnected performance drivers to be viewed in common throughout the organization" (Pauwels 2014, p. 7). Figure 3 shows the dashboard that Inofec managers used to project the expected profits expected from changes to price discounts and to offline and online marketing communication, which created the organizational buy-in to run experiments demonstrating actual profit hikes (Wiesel, Arts, and Pauwels 2011).

Such communication tools make it possible to integrate diverse business activities (some of them qualitative) with performance outcomes. This helps managers in at least five ways (Pauwels 2014). First, a dashboard enforces consistency in measures and measurement procedures across departments and business units. For example, Avaya provides business communication solutions in over 50 countries and diverse markets, with varying marketing tactics. Before the dashboard project, the company had no commonality of systems around the globe, it used different definitions of what constituted a "qualified lead" (a key performance metric in the handoff from marketing to sales for business-to-business companies), and there was a lack of regional interest in gathering metrics.

Second, a dashboard helps monitor performance. Monitoring may be both evaluative (who or what performed well?) and developmental (what have we learned?). Google provides a good example: dashboard metrics are early indicators of performance, and if a dip occurs in, for example, the trust-and-privacy metric, the company takes corrective action.

Third, a dashboard may be used to plan goals and strategies. For example, TD Ameritrade's corporate scorecards, developed by the strategic planning department, led to a dashboard that plugs into the planning cycle and is tied to quarterly compensation.

FIGURE 3
Marketing Analytic Dashboard for Inofec



Source: Pauwels (2014).

Fourth, a dashboard may be used to communicate to important stakeholders. The dashboard communicates not only performance but also, through the choice of metrics, the things an organization values. Vanguard's dashboard, for example, enabled it to share with its corporate board its focus on customer loyalty, feedback, and word of mouth.

Finally, a dashboard offers a good starting point for important discussions, such as when management sets stretch targets without providing additional resources. For instance, the U.S. division of an automotive company was instructed to increase profits despite longer innovation cycles and lower advertising budgets. Analytics and dashboard tools helped the division present what-if scenarios and make its case to headquarters that trade-offs were necessary by quantifying the relation between marketing actions and profits.

Dashboards also allow for more effective communication with marketing partners, especially as companies move to performance-based compensation of agency work. As the sales impact of performance metrics may differ across countries, managers should use dashboard insights to set specific metric targets (Pauwels, Erguncu, and Yildirim 2013). In the case of the U.S. division of the aforementioned automotive company, brand consideration was a more important performance metric in an emerging market, while brand liking was more important in a mature market. Further research is needed to generate empirical generalizations and boundary conditions in this regard.

Adapting Communication to the Style of the Decision Maker

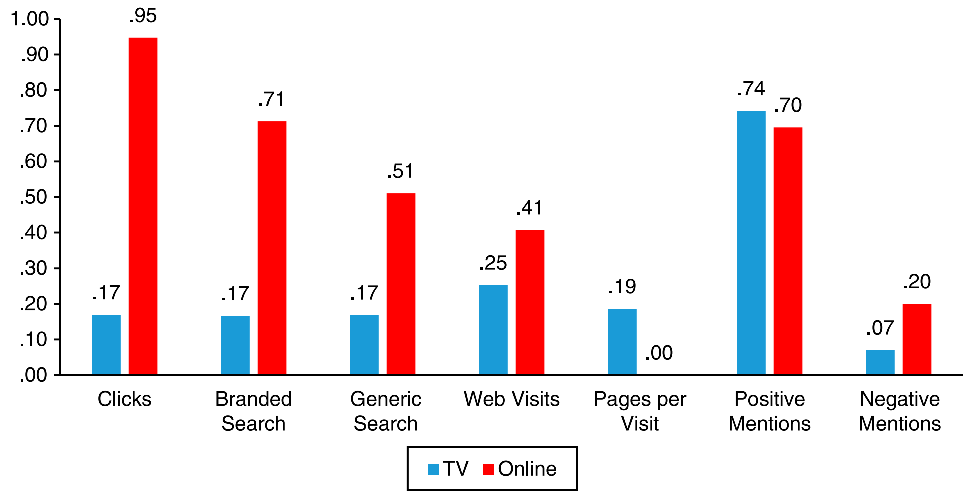
In their review of ISMS-MSI Practice Prize finalists, Lilien, Roberts, and Shankar (2013) detail the characteristics of successful marketing science applications. They advocate estimating simple, easy-to-use models and obtaining organizational buy-in through, among other things, speaking the same language as influential executives. Marketing analytics customers strongly differ in their decision-making language, with some companies favoring a more analytic style and others using a more intuitive style. We recommend communicating marketing analytics according to the company's style.

When decision makers have a more analytical style, presenting estimates and elasticities straight from the analytics helps them understand exactly what is going on and how decision optimality is affected—for example, when deciding how to allocate marketing budgets by drawing on their relative elasticities. Even in such cases, though, it is best to provide the proper context—for example, by comparing the effects that television advertising elasticities and online advertising elasticities have on online performance metrics, as Figure 4 shows.

Decision makers with a more analytical style require more information on the analytics assumptions and the uncertainty around the performance projections. Academic researchers are typically well versed in such explanations. In contrast, decision makers with a more intuitive decision style may be averse to discussions on confidence intervals, functional form, and error distribution assumptions. Communicating analytics insights in such environments requires more visualization, such as the heat map of the projected profit consequences of changes to marketing actions shown in Figure 5.

Figure 5 shows the highest profit (8.51; units disguised) as a specific combination of price ($45) and advertising budget ($3.25 million) but also communicates how close other combinations are to this maximum projected profit. For instance, at a current price level of $35, the decision maker may feel uncomfortable with prices over $40, perhaps fearing a customer backlash not included as a model variable. The decision maker can look up the highest possible profit and associated marketing actions for prices below $40. After adjusting the price in this model-suggested direction, more

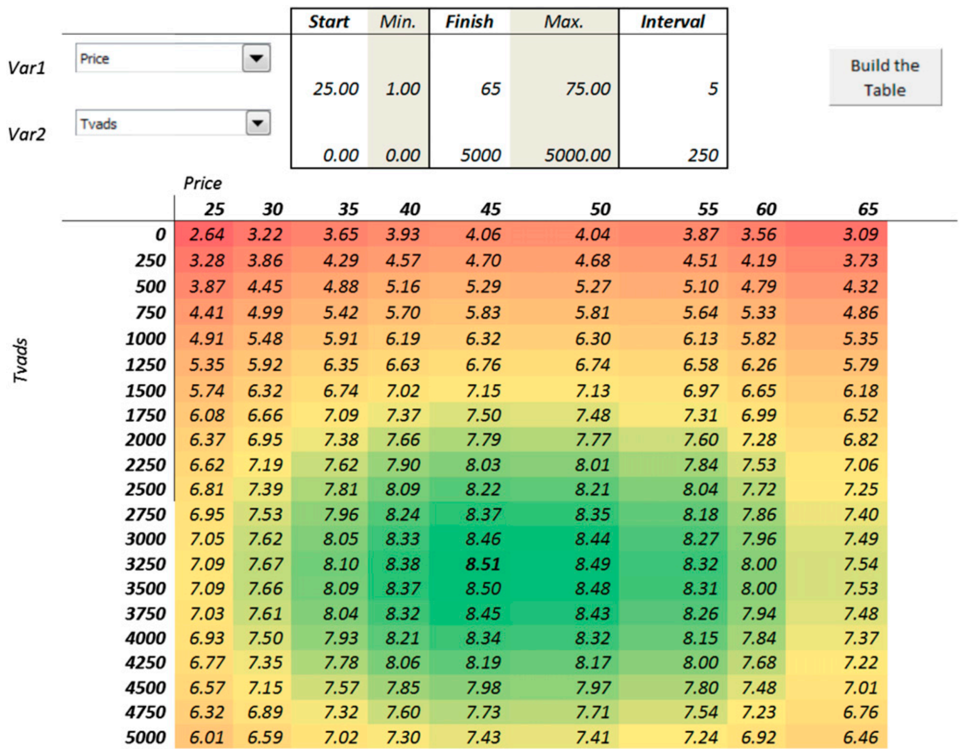
FIGURE 4
Comparison of Television and Online Marketing Elasticities on Online Performance Metrics



Source: Pauwels and Van Ewijk (2013).

data and insights will then be available for recalibration of analytics and intuition. Alternatively, the decision maker might decide to allocate only the $2 million communication budget provided by his or her superior, the investor (see Table 1). The heat map provides the decision maker with not only the best outcome under the given budget (a projected profit of 7.79) but also a quantitative argument for why profits can be increased (up to) 9% if the advertising budget is increased toward its optimal level. As such, the heat map enables decision makers to tweak model-derived optimal allocations, which provides a level of decision comfort. Decision comfort has been shown to be an important contributor to managers' willingness

FIGURE 5
Profit Heat Map of the Interaction of Price and Advertising



		Start	Min.	Finish	Max.	Interval
Var1	Price	25.00	1.00	65	75.00	5
Var2	Tvads	0.00	0.00	5000	5000.00	250

Build the Table

Tvads \ Price	25	30	35	40	45	50	55	60	65
0	2.64	3.22	3.65	3.93	4.06	4.04	3.87	3.56	3.09
250	3.28	3.86	4.29	4.57	4.70	4.68	4.51	4.19	3.73
500	3.87	4.45	4.88	5.16	5.29	5.27	5.10	4.79	4.32
750	4.41	4.99	5.42	5.70	5.83	5.81	5.64	5.33	4.86
1000	4.91	5.48	5.91	6.19	6.32	6.30	6.13	5.82	5.35
1250	5.35	5.92	6.35	6.63	6.76	6.74	6.58	6.26	5.79
1500	5.74	6.32	6.74	7.02	7.15	7.13	6.97	6.65	6.18
1750	6.08	6.66	7.09	7.37	7.50	7.48	7.31	6.99	6.52
2000	6.37	6.95	7.38	7.66	7.79	7.77	7.60	7.28	6.82
2250	6.62	7.19	7.62	7.90	8.03	8.01	7.84	7.53	7.06
2500	6.81	7.39	7.81	8.09	8.22	8.21	8.04	7.72	7.25
2750	6.95	7.53	7.96	8.24	8.37	8.35	8.18	7.86	7.40
3000	7.05	7.62	8.05	8.33	8.46	8.44	8.27	7.96	7.49
3250	7.09	7.67	8.10	8.38	8.51	8.49	8.32	8.00	7.54
3500	7.09	7.66	8.09	8.37	8.50	8.48	8.31	8.00	7.53
3750	7.03	7.61	8.04	8.32	8.45	8.43	8.26	7.94	7.48
4000	6.93	7.50	7.93	8.21	8.34	8.32	8.15	7.84	7.37
4250	6.77	7.35	7.78	8.06	8.19	8.17	8.00	7.68	7.22
4500	6.57	7.15	7.57	7.85	7.98	7.97	7.80	7.48	7.01
4750	6.32	6.89	7.32	7.60	7.73	7.71	7.54	7.23	6.76
5000	6.01	6.59	7.02	7.30	7.43	7.41	7.24	6.92	6.46

Source: Pauwels (2014).

to adopt analytics in decision making (Parker, Lehmann, and Xie 2016).

As for the danger of analytics users misunderstanding the model's assumptions, note that the heat map in Figure 5 restricts the decision maker's range of potential price and advertising levels. Contacts at the company preferred this restriction on the range of the past data rather than show increasing confidence intervals as users consider options farther away from the mean(s) of past marketing level(s). The contacts felt that although the latter might be appropriate for decisions makers with an analytical style and background, it would confuse other decision makers to the point that they might not trust or use the model.

Empirical studies have shown that intuition may be better than analysis in certain conditions—for example, for novices under time pressure to make complex decisions (Wierenga 2011). Further research is needed to specify such conditions for marketing decisions and to show how intuition and analysis interact.

Adapting Communication to the Marketing Organization

Beyond decision-making styles, the structure and organization of the marketing team matters in communication about marketing analytics. At least one analyst should be included in a decision-making team. During discussions about, for example, increasing spending on a marketing action, the analyst could remind others that it has a small sales elasticity. Such early inclusion of analytics insights may reduce decision makers' resistance to model-based objections to proposals in which they are emotionally invested; moreover, it may help companies guard against the tendency of decision makers to cherry-pick the data and models that generate results supporting a priori beliefs (Soyer and Hogarth 2015). An example at a high strategic level is the appointment of an algorithm to the board of directors of a venture capital company (Wile 2014). In this way, analytics has an independent vote in deciding which new venture proposals to fund and can break the tie when the human voters are split.

Conclusions

The multidimensional nature of marketing is expressed in a variety of performance metrics—attitudinal, behavioral, and financial—that turn out to be weakly interrelated. This makes it difficult to assess marketing's value and often results in skepticism about marketing's contributions and a reduction in the role of marketing at senior levels of decision making. As the digital age marches on, new marketing applications are created (e.g., mobile targeting), which may enable marketing to occupy an increasingly tactical function in organizations.

This has led us to study marketing value assessment from three perspectives: metrics, models, and communication. Following the chain of marketing productivity (Figure 1), we postulate that successful marketing value assessment needs to reconcile the different performance metrics that are available, combine historical data analysis with marketing experiments, and significantly enhance the communication of analytical results to an audience of decision makers who are not analytically oriented. Marketing educators can help bridge this gap by integrating the assessment and the communication of marketing value in their teaching. The current growth in marketing and business analytics programs offers a clear opportunity in this regard.

We offer a brief review of what is currently known about metrics, models, and communication, along with suggestions for specific avenues for further research. First, we know that market orientation and the use of marketing metrics improve marketing performance, but we do not yet know how this marketing performance (as opposed to marketing communication) drives the scope of marketing in the organization. Second, we have rules for optimizing profits and sales, but not for weighting different marketing objectives. Third, we know how to measure effectiveness and efficiency, but not the conditions under which each is most appropriately pursued, nor do we know when it is best to use automated marketing programs (which focus on efficiency). Fourth, empirical generalizations regarding response elasticities enable us to optimize marketing allocations in the short run, but not yet to quantify marketing synergies for organic growth, nor to identify which conditions favor top-down allocations and which favor bottom-up allocations.

Fifth, we know a lot about marketing elasticities on hard performance metrics but know little about how marketing affects soft performance metrics and how these relate to hard performance under different conditions. Still unknown is whether the complicated relation between soft performance metrics and sales is better characterized by strong average effects with large confidence intervals (high elasticity with high noise) or by small average effects with tight confidence intervals (low, precise elasticity). Furthermore, we need to detect and explain outlier brands that buck the average relationship among metrics (Ailawadi and Van Heerde 2015). Sixth, risk has been decomposed in terms of performance variance but is not yet quantified in the timing of these performance returns. Moreover, we are limited in the advice we can provide on the risk of stopping marketing activities and optimal competitive reaction. Finally, we know several generalities about communicating marketing value (e.g., visualizations), but we have little insight into success factors for different communication methods and for intuitive and analytical decision making.

Our overall conclusions are as follows. First, marketing value assessment is essential if marketing as a discipline wants to exert an influence at the highest levels of the organization. Its influence will also determine the scope of its role in the organization, which could range from tactical execution of advertising and promotion policies to being a fundamental driver of organic growth.

Second, significant advances in data quality and quantity, along with new analytical methods, have served marketing value assessment well both in academia and in industry. Most of these advances have occurred at the tactical level. In particular, digitization allows for a much improved understanding of the connection between soft (attitudinal) and hard (transactional) metrics.

Third, marketing analytics technology has been used mainly for resource allocation decisions, not investment decisions. Media mix and digital attribution models, for example, are widely accepted and used. This evolution pushes marketing practice in an automated, programmatic direction, not unlike the automated trading of securities on Wall Street. It also necessitates the use of visualization methods to successfully communicate the complexities of marketing value creation.

Finally, to better serve the strategic aspect of marketing, which is the key interest of senior management in the organization, databases will need to be better integrated across the elements of the marketing mix, broadly defined. This presents an opportunity for providers of enterprise resource-planning solutions: by including customer and marketing data in their systems, they can provide a unified data platform that will allow for a cross-functional view of marketing and the value of marketing in the organization.

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