

Forward-Looking Focus

Can Firms Have Adaptive Foresight?

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Customer metrics are pivotal to assessing and monitoring how firms perform with customers and other publics. The authors contend that customer metrics used by firms today are predominantly rear-view mirrors reporting the past or dashboards reporting the present. They argue that companies need to and can develop “adaptive foresight” to be positioned to predict the future by exploiting changes in the business environment and anticipating customer behavior. They address the need for adaptive foresight by synthesizing and integrating literature on customer metrics, customer relationship management, customer asset man-

agement, and customer portfolio management. They begin by reviewing the metrics that have been and are currently being used to capture customer focus. Next, they discuss possible “headlight” or forward-looking customer metrics that would allow firms to anticipate changes and provide opportunities to increase the value of the customer base. They then identify the conditions under which the new metrics would be appropriate and offer a process for developing adaptive foresight. The authors close by discussing the implications of adaptive foresight for successful customer asset management that increases long-run business performance.

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Managers have made an intensive effort to measure the impact of marketing on business performance (cf. Lehmann 2004). Recently, customer asset management or customer relationship management (CRM) metrics have been proposed as a means for firms to continuously monitor—and manage—the expected future value of the firm (Gupta and Lehmann 2005; Rust, Lemon, and Zeithaml 2004). CRM focuses on two business performance outcomes: the creation of value for shareholders and the creation of value (i.e., utility) for customers (Boulding et al. 2005; Payne and Frow 2005; Vargo and Lusch 2004). These two outcomes are considered to be congruent because customer relationships represent market-based assets that increase shareholder value by accelerating and enhancing cash flows, lowering the variability of cash flows, and increasing the residual value of cash flows (Srivastava, Shervani, and Fahey 1998).

CRM metrics provide a way to assess the current value of the (total) customer base or “customer equity.” For example, customer equity can be calculated from three underlying sources: customer acquisition, retention, and gross margins. Gupta, Lehmann, and Stuart (2004) used publicly available information from financial statements to calculate the (post tax) customer-based value of five companies and found that their estimates were reasonably close to the reported market values (i.e., value for shareholders) for three firms, and significantly lower for two firms (Amazon and eBay). More important, recent research has revealed that CRM metrics are—in some situations—leading indicators of the expected future value of the customer base. For example, customer satisfaction has been found to be positively associated with the growth and stability of a firm’s future cash flows (Anderson, Fornell, and Mazvancheryl 2004; Gruca and Rego 2005).

Marketers have been intrigued and excited by the notion that CRM metrics can provide managers with a glimpse of the firm’s future value under different scenarios—perhaps even when the business environment is radically different. This knowledge of the future, which we term *adaptive foresight*, is crucial if managers are to make appropriate investment decisions and (ultimately) realize forecasted cash flows and earnings streams. Consider, for example, the success with which Dell Computer revolutionized the way customers (and organizations) purchase computers. What capabilities, measures, or research enabled Dell to foresee that customers and firms would flock to a process that allowed simplified customization, direct ordering, and consistent access and communication regarding orders and equipment? Can firms, using forward-looking customer metrics, identify key trends (such

TABLE 1
Existing Customer Needs
Versus Unanticipated Needs

	<i>Existing Needs or Anticipated Needs</i>	<i>New Needs (Not Anticipated)</i>
New customers	Acquisition	New market opportunity Exploited or overlooked
Existing customers	Retention	Market expansion or contraction
Customer-based value of the firm	Customer lifetime value (CLV)	CLV higher or lower than anticipated

as disintermediation and customization in the personal computer industry) before they happen? It is important to recognize, however, that firms operate in a dynamic environment with considerable uncertainty. Customer preferences change, competitors’ actions are unpredictable, and the business environment can be volatile. These conditions create a challenge: What metrics can help managers anticipate, prepare for, and exploit changes in the marketplace that will influence the future value of the firm?

This challenge can be shown by a simple illustration. Table 1 compares a scenario in which customer preferences change—that is, new needs emerge that are unrecognized by the firm—with a scenario in which they do not. As shown in the middle column, when managers assume the firm will continue to provide value to customers so that the sources of value for the firm (customer acquisition, retention, and margins) remain stable or (at best) change by modest amounts, it is relatively straightforward to calculate the expected future value of the customer base. In the right column, managers do not recognize that new needs will emerge, so their estimates of expected value of the customer base are faulty. Moreover, they are unable to identify the investment opportunities that will prepare for and exploit the coming changes.

This article considers how companies can develop adaptive foresight, so that they are positioned to exploit changes in the business environment. We will attempt to answer four questions:

1. What customer metrics have been and are currently being used to capture customer insights, and how effective are they?
2. Are there other “forward-looking” customer metrics that would be effective in helping firms anticipate changes and provide opportunities to increase the value of the customer base?
3. Under what conditions will these new metrics be appropriate?
4. What are the implications of these insights for successful customer asset management that increases long-run business performance?

We will address these questions by synthesizing and integrating literature on customer metrics, CRM, customer asset management, and customer portfolio management—as well as summarizing key findings. Note that we focus on customer metrics, rather than considering how to anticipate competitor actions, because there has been recent research on the latter topic (cf. Ailawadi, Kopalle, and Neslin 2005; LeeFlang and Wittink 1996; Steenkamp et al. 2005). We will also discuss emerging trends and issues as well as likely future developments (both theoretical and methodological) and suggest areas where further research is needed.

CURRENT CUSTOMER METRICS: REAR-VIEW MIRRORS AND DASHBOARDS

An examination of the current state of the art in customer metrics reveals severe limitations. The first and most critical deficiency is that most current customer metrics reflect the past, or at best the present, aspects of customer focus. To elaborate, we will describe the four categories of customer metrics that are used today: perceptions, overall judgments, behaviors, and financial measures. We will also discuss the extent to which they capture the past, present, or future.

Rear-View Mirrors

Metrics that capture the past are rear-view mirrors, retrospective snapshots of the ways customers have evaluated the company, its employees, or its products and services in the past. Customers' perceptions and overall judgments are the rear-view-mirror measures that were developed and used heavily by companies in the 1990s.

Perceptions are customer beliefs about the attributes and performance of products and services. Customer judgments are overall assessments, such as customer satisfaction, perceived quality, perceived value, loyalty, or attitudes toward the brand or organization. These metrics have been adopted for many reasons. First, because they are collected almost exclusively through surveys, they have been relatively easy to obtain and share. Methodologies and best practices were developed in companies and in marketing research organizations during the 1990s. Second, using these metrics as dependent variables allowed companies to assess the key attribute drivers that could then be addressed by specific marketing and operational strategies within a company. Third, the measures helped companies track performance over time, benchmark against competitors' offerings, and compare performance across different parts of an organization (e.g., branches, units, territories, countries).

Customer satisfaction is the most widely used perceptual metric because it is generic and can be universally gauged for all products and services (including nonprofit and public services). Even without a precise definition of the term, customer satisfaction is clearly understood by respondents, and its meaning is easy to communicate to managers. Both in practice and in academic research, customer satisfaction has been measured at the transaction level (as in trailer or event-triggered surveys) and at the overall level (as in the American Customer Satisfaction Index). In early studies, academics often focused on measuring confirmation/disconfirmation and expectations, where expectations have been defined as predictive expectations (Oliver 1997; Tse and Wilton 1988), desires (Westbrook and Reilly 1983), and experience-based norms (Cadotte, Woodruff, and Jenkins 1987). Applied marketing research tends to measure satisfaction both ways, at the transaction level but more frequently as an overall evaluation, a cumulative construct that is developed over all the experiences a customer has with a firm.

Service quality has also been widely measured since the mid-1980s, but it is not as prevalent as customer satisfaction because it is limited to examining the intangible aspects of an offering. To a far lesser extent, constructs such as commitment, repurchase and referral intentions, perceived value, and trust have made their way into company measurement systems and academic research (cf. Bolton, Lemon, and Verhoef 2004; Verhoef 2003). In contrast, attitudinal measures are frequently used to measure the degree of attraction that customers have either to brands of the company as a whole. Brand metrics are often designed to capture awareness, image, liking, and/or reputation of the brand or firm. Some of these perceptual measures, particularly perceived value, are more ambiguous constructs and are difficult to operationalize. Gupta and Zeithaml (2006) provided an overview of other commonly used perceptual measures and discussed their limitations.

Perceptual and attitudinal measures have disadvantages as metrics. All are retrospective: By the time we get the data from customer surveys, they represent yesterday rather than today. Perceptual measures also typically focus only on current customers, ignoring noncustomers whose perceptions are likely to be as important—or more important—than current customers. Most of these measures do not incorporate competition and therefore cannot reflect or anticipate marketplace changes. In recent years, companies are also finding that the most common metrics, customer satisfaction and repeat purchase intentions, cannot completely explain or predict behavior. Many satisfied customers defect, and generating satisfied customers does not directly translate into the company-preferred customer behaviors and consequently revenues and profits.

TABLE 2
Four Categories of Customer Metrics

	<i>Examples of Metrics</i>	<i>Firm User of Metric</i>	<i>Database</i>	<i>Ability to Predict Performance</i>
Perceptions	Customer satisfaction Service quality Commitment Perceived loyalty Behavior intentions	Frontline employees Midlevel supervisors Unit managers	Customer satisfaction database	Moderate
Attitudes	Awareness Interest Knowledge Desire	Marketing/advertising department	Brand advertising Database	Low
Behavior	Customers acquired Customers retained Cross-selling Word of Mouth	Salespeople	Operations database Customer relationship management database	Moderate
Financial measures	Customer lifetime value Customer equity	Salespeople Accounting Finance CEO/CFO	Finance database	Moderate

From Rear-View Mirrors to Dashboards

Recognizing that one or a few perceptual measures were insufficient to understand the customer, companies, such as The Vanguard Group, have developed more comprehensive batteries of customer metrics commonly known as dashboards (cf. Reibstein et al. 2004). These dashboards incorporate both retrospective measures such as customer satisfaction but also include operational and behavioral measures that can be accessed and reported in real time. Operational measures are especially useful for service organizations. They tend to be idiosyncratic to the firm or industry but typically include trouble reports or complaints, response times, resolution times, waiting times, yield or capacity measures, engineering measures, and so forth. There is some recent evidence that these measures can predict future customer behavior (e.g., Bolton, Lemon, and Bramlett in press).

As database management and CRM have evolved, researchers and companies have measured customers' observed behavior. Behavioral metrics focus on customers' decisions of what, when, how much, and how long to continue to buy a product or service. The metrics most frequently used include number of acquired customers, "churn" as a percentage of the customer base (the inverse of the customer retention rate), the dollar value of cross-selling, the percentage increase in customer migration to higher margin products, and sometimes word-of-mouth activity. These metrics are easier to compile and access than most perceptual measures but also vary in the ease with which they are defined and

calculated. These metrics are discussed in more detail later in this article.

Predicting Future Performance From Perceptions, Attitudes, and Behaviors

At best, we could say that perceptions, attitudes, and behaviors can only partially predict future levels of the metrics themselves (i.e., how many customers we will acquire in the future) or financial performance (i.e., what the profit impact of changes in the metrics will be) (see Table 2). Table 2 shows that each of these three categories of metrics is typically used by different groups in companies for different purposes and has different limitations. Customer satisfaction is used more for tactical than strategic reasons. It is a good feedback mechanism for employees so that managers can record, motivate, and compensate performance. For that reason, midlevel supervisors and managers are primary users of customer satisfaction metrics. Satisfaction is also used by unit managers to compare across branches, units, or outlets of a company to determine relative performance and compensate the units. Satisfaction measures are typically housed in a customer satisfaction database or outsourced to marketing research firms and are rarely used by companies in predictive modeling. However, academic research has consistently shown that there is a positive relationship between customer satisfaction and diverse business performance metrics, as discussed later in this article.

Attitudinal measures are typically collected in a marketing research department and are used to show the

impact of company advertising, public relations, and other promotional vehicles on reputation or brand image. These are collected both on current and potential customers. Because advertising models have been developed and used for a long time, many companies are able to leverage them in sophisticated ways (Keller 2000). The departments of the company that tend to use attitudes are the marketing and advertising departments. Importantly, academics have recently linked certain brand attitude measures that are frequently used by companies to shareholder value (Mizik and Jacobson 2005).

Behavioral metrics are contained in an operations database and used and reported most often to salespeople and sales managers along with metrics about revenues. With the advent of CRM systems, companies have been able to build complex direct marketing models. Finally, customer financial measures, collected much more recently and less frequently by firms, are contained in the CRM database.

Perceptual, attitudinal, and behavioral metrics are housed in different databases and used by different groups in the organization, so they are rarely integrated or linked with financial measures. For this reason, many companies face significant hurdles to building models that predict business performance from customer measures. In contrast, academic researchers have constructed theory-based models that forecast future individual customer behaviors—that is, trial, repeat purchases, cross-buying, and switching behavior—and that are then used to calculate individual customer profitability (e.g., Bolton, Lemon, and Verhoef 2004). There are several alternative models for predicting the length of an individual customer's relationship with a firm (e.g., Bolton 1998; Reinartz and Kumar 2000; Thomas 2001). However, there are fewer models that predict purchase quantities and cross-buying behavior. Notable exceptions include studies by Bolton and Lemon (1999); Kamakura, Ramaswami, and Srivastava (1991); and Verhoef, Franses, and Hoekstra (2001). A significant challenge in specifying such models is that some individual customer behaviors, such as customer retention, purchase frequency and recency, as well as cross-buying, may be simultaneously determined (cf. Thomas and Reinartz 2003).

If the models are sufficiently sophisticated, they can account for anticipated changes in the business environment (e.g., increased word-of-mouth behavior), as well as planned marketing actions (Hogan, Lemon, and Libai 2004). For example, Lewis (2005) estimated a structural dynamic programming model to simulate customer response to marketing programs over an extended time period, thereby providing an estimate of customer equity that is directly connected to firm decisions (e.g., marketing actions).

MOVING FROM DASHBOARDS TO HEADLIGHTS: LEADING INDICATORS OF CUSTOMER VALUE TO THE FIRM

The premise of this article is that forward-looking metrics are more desirable to firms than retrospective or real-time metrics. Forward-looking metrics could be called headlights, as they project where customers are going rather than where they have been. Few of these measures exist today, the closest being customer lifetime value (CLV) and customer equity.

Customer Lifetime Value Metrics

Firms typically focus on the value the customer provides to the firm or CLV, calculated as the sum of the discounted net contribution margins over time of the customer—that is, the revenue provided to the company less the company's cost associated with maintaining a relationship with the customer (Berger and Nasr 1998). Prior research has typically used past behavior and marketing actions to predict future behavior, incorporating future uncertainty through the retention rate and discount rate. Most firms are unable to perfectly predict the cash flows associated with an individual customer, but they can calculate the expected value of the cash flows (adjusting for risk) associated with an individual customer conditional on the customer's characteristics, the company's planned marketing actions, and environmental factors (Hogan et al. 2002; Jain and Singh 2002).

Calculating Customer Equity

Firms can calculate the expected value of the total customer base by aggregating CLV across customers—yielding “customer equity” (Blattberg, Getz, and Thomas 2001; Rust, Lemon, and Zeithaml 2004). Alternatively, customer equity can be calculated at the aggregate level, from its three underlying sources: customer acquisition, retention, and gross margins (cf. Blattberg and Deighton 1996; Gupta and Lehmann 2005). To obtain more precise estimates, these three sources can be estimated at the segment or cohort level (i.e., representing homogeneous customer groups) and then aggregated. Many researchers assume a constant aggregate retention rate (Berger and Nasr 1998; Gupta and Lehmann 2003).

CRM Metrics

CRM systems typically provide metrics based on past purchase behavior or business performance. In database marketing applications, these metrics typically include number of acquired customers, the customer retention rate,

the dollar value of cross-selling, the percentage increase in customer migration to higher margin products, and the profitability of individual customers or customer segments. In practical applications, there is a great temptation to assume that metrics based on past business performance are good predictors of future customer equity. Unfortunately, there is substantial empirical evidence that measures of past customer profitability (alone) are not necessarily good predictors of future customer profitability (Campbell and Frei 2004; Malthouse and Blattberg 2005).

It is possible to obtain more accurate predictions of the future profitability of individual customers by incorporating the firm's marketing actions as additional predictor variables (e.g., Venkatesan and Kumar 2004). However, models that treat individual customer profitability as a dependent variable are (from a theoretical standpoint) inherently misspecified because individual customer profitability is a composite measure calculated from individual purchase behaviors and financial identities (e.g., margins), summed across products—where each component will have different antecedents. These models can be useful for prediction in some practical contexts (especially when market conditions are relatively stable), but they are less useful for describing how outcomes arise from changing market conditions.

Approaches to Forecasting Customer Equity

As we have previously discussed, academic researchers have constructed theory-based models that forecast future individual customer behaviors—that is, trial, repeat purchases, cross-buying, and switching behavior—and that are then used to calculate individual and aggregate customer revenues/profitability. However, there is also a substantial body of research that attempts to build models that predict customer equity or shareholder value based on a limited set of customer metrics. For example, cross-sectional research has shown that improvements in customer satisfaction have significant and positive impact on financial performance. Most of this research uses the American Customer Satisfaction Index (ACSI) customer satisfaction database and links perceptions to publicly reported financial measures of company performance. Research shows a link between ACSI and firm value (Anderson, Fornell, and Mazvancheryl 2004), market value (Ittner and Larcker 1998), return on assets (ROA) (Hallowell 1996), return on investment (ROI) (Anderson and Mittal 2000), return (Rucci, Kim, and Quinn 1998), and cash flow (Gruca and Rego 2003). However, these findings have been shown to vary across industries, with the link between ACSI and market value positive but nonsignificant for durable and nondurable manufacturing firms; positive and significant for transportation, utility, and communication firms; and negative for retailers.

In contrast, Rust, Lemon, and Zeithaml (2004) have developed a comprehensive model of customer equity that can be operationalized with a single firm's data. They modeled customer equity as a function of three drivers that they term value equity, brand equity, and relationship equity. These drivers involve variables such as product and service quality, awareness of a brand, attitude toward the brand, and membership in a loyalty program. Their approach is novel because each predictor is measured by surveying customers about past relationships and transactions involved with the brand, the loyalty program, and the perceived quality of the product; plus they utilized a brand-switching matrix that accounts for competition.

Forecasting Customer Equity Under Different Future Scenarios

The basic approach to evaluating investment opportunities is straightforward: The firm calculates the expected future value of the customer base under alternative scenarios and selects the scenario with the most attractive risk/return profile. This approach has been embedded in tools that help managers' evaluate a wide range of investment opportunities (cf., Rust, Lemon, and Zeithaml 2004). In this way, firms are able to forecast customer equity based on their planned actions. For example, if a firm intends to invest in a customer satisfaction program that should increase its retention rate, the expected value of its customer base will be higher than if it did not make the investment.

It is relatively straightforward (from a conceptual standpoint) to forecast customer equity conditional on changes due to firm decisions. However, the forecast is more complicated when the manager must consider factors (i.e., customer preferences, competition, and business environment) that are not under the firm's control (cf. Ailawadi et al. 2005; Leeflang and Wittink 1996; Steenkamp et al. 2005). In most cases, when marketers wish to explicitly recognize risk factors (other than deflection), they use a risk-adjusted discount rate rather than a weighted average cost of capital in their CLV calculations. Hogan et al. (2002) suggested that this task could be accomplished by either measuring the variance of returns over time for various segments and calculating the appropriate discount rate—analogue to the evaluation of real options (Copeland and Antikarov 2001)—or decomposing customer profitability into additional sources.

Leading Indicators of Customer Equity

Researchers are working to identify methods to incorporate risk factors or anticipated changes arising from customer preferences, competition, and the business

TABLE 3
Comparison of Value of Customers
to the Firm With Value to Customers

	<i>Low Value to Customers</i>	<i>High Value to Customers</i>
High value of customers	Vulnerable customers	Star customers
Low value of customers	Lost causes	Free riders

SOURCE: Gupta and Lehmann (2005, p. 44).

environment into CLV forecasts. Until these methods are further developed, forecasts of customer equity cannot be considered leading indicators of the value of the customer base—and they are certainly not widely utilized. Many firms use proxy variables that they believe are good predictors of future purchase behavior or profitability. These proxy variables are typically (aggregated) survey measures, such as service quality, satisfaction, value, and repeat purchase intentions.

There is substantial empirical evidence supporting the use of customers' quality or satisfaction ratings as leading indicators of customer equity. For example, Kordupleski, Rust, and Zahorik (1993) reported that aggregate quality ratings lead market share for one division of AT&T by about four months. Danaher and Rust (1996) found that overall service quality is positively associated with cellular service usage rates. However, customer satisfaction has the best "track record" as a leading indicator of customer equity. As we have already discussed, longitudinal studies have shown that satisfied customers are more likely to be retained, buy more, and cross-buy, and numerous cross-sectional studies have linked ACSI to publicly reported financial measures of company performance. These results are both surprising—because customer satisfaction is a retrospective measure—and reassuring because they support conventional practices.

Next Steps

Although some progress has been made, researchers have not (yet) identified many forward-looking metrics that can guide decision making. It is true that marketers have developed some tools to guide investment decisions and some individual metrics that can serve as predictors of CLV or customer equity. However, these approaches are only useful in situations where customer preferences, the competition, and the business environment remain relatively stable or change in well-defined ways (usually the firm's marketing actions change). In addition, different approaches are useful in different contexts, as can readily be seen by comparing approaches used in direct marketing versus continuously provided service contexts.

Perhaps it is unreasonable to believe that any single measure can predict the future value of the customer to the firm in all practical contexts. A more fruitful approach may be to consider whether a constellation of metrics—considered in conjunction with each other—might provide a future-oriented view of the marketing landscape.

To manage customer equity, Gupta and Lehmann (2005) argued that firms should allocate more resources to customers who yield a high value to the firm and who perceive the firm's offerings to have a high value (see Table 3). Vulnerable customers may defect to competitors unless the firm develops an appropriate marketing program to retain them; free riders should receive lower product quality and higher prices. In the next section, we will suggest that the "best" way to predict the future value of the customer to the firm may be to *anticipate* how the firm can provide value to the customer—where this information can be used to guide the firm's attempts to capture value from customers, thereby realizing shareholder value.

LEADING INDICATORS OF FIRM VALUE TO THE CUSTOMER

In the previous section we listed indicators of the value a firm hopes or anticipates that it will receive from its current or potential customers. In this section we list measures of what—in equilibrium—should be the same stock of value: what the customers hopes or anticipate that they will receive from the firm (MacInnis and de Mello 2005). By approaching valuation from both the firm and the customer side of the exchange, we hope to avoid the risk of unjustified optimism. If the firm's hope of value from the customer deviates from the customer's hope of value from the firm, only the lower of the two can be relied on.

What is it that, conceptually, is meant by a customer's hope of future value? We argue for two dimensions: (a) predictions of transactional value and (b) the customer's optimism or pessimism regarding the trajectory of the relationship. If the customer thinks of the firm purely transactionally, as a target for some future exchange in which the "give" will be equal to or less than the "get," the assessment of future value is straightforward. It is indicated by a standard measure of current purchase intent or attitude to the firm. If, however, the customer sees the firm both as a transaction candidate but also as capable of learning about their tastes or needs, or more generally willing to engage relationally, the hope of future value may be substantially greater than the current purchase intent. Therefore, our conceptualization of leading indicators of customer sentiment requires attention to the distinction between transactional and relational exchange and requires us to identify the markers of relationality.

Although it seems sensible to consider purchase intentions as useful predictors of purchase behavior, several studies have demonstrated this relationship is not very strong. However, the relationship can appear strong because measurement inflates the association between intentions and behavior (Chandon, Morwitz, and Reinartz 2005; Morwitz and Schmittlein 1992). As we might expect, purchase intentions will not be good predictors of future behavior when circumstances (competition, the business environment, customer preferences) change, as they inevitably will, in the short, medium, or long term. This insight was highlighted in a recent study by Seiders et al. (2005), who showed that the relationship between customer satisfaction and repurchase behavior is contingent on the moderating effects of convenience, competitive intensity, customer involvement, and household income; whereas the relationship between customer satisfaction and repurchase intentions is not. Whereas customers' intentions can change from day to day or even hour to hour, and whereas customers may not be able to clearly specify their future preferences/tastes or needs, the most fruitful approach may be predicting how customer preferences will change over time.

Transactional and Relational Exchange

Exchanges can be considered to span a continuum from transactional to relational (Dwyer, Schurr, and Oh 1987). In a transactional exchange, the "give" of the exchange is foreseen by each party to be fair compensation for the "get." By the end of the transaction, the parties expect to have extracted mutual gains from the trade, and the fact that there is an end point is one of the defining elements of transactional exchange. For relationships, by contrast, duration is open-ended, and at various points of time one or the other party might be "in debt" to the other. Because of this indebtedness, the identities of the parties matter, as do their reputations. A transaction can be anonymous, but not a relationship. Indeed, the growth of a relationship can be monitored by the increasing richness of identity and by the quality of reputation.

As exchange becomes more relational, at any instant one or other party may be receiving more than the other and so either party is vulnerable to loss. Tolerated vulnerability has long been acknowledged as a marker of relationality (Deutsch 1958; Moorman, Deshpandé, and Zaltman 1993). Fournier (Aaker, Fournier, and Brasel 2004; Fournier, Dobscha, and Mick 1998) has shown that strong relationships are often ones of mutual vulnerability. She offered the word *transgression* as a collective noun for all the ways a seller can hurt the process of relationship development, wind back the skein of reputation, and render intolerable the vulnerability and identity that together builds the intensity of a relationship.

Indicators of Relationship Strength

In the previous section, we proposed that the customer's assessment of the value of a firm is indicated by purchase intent and hope for the relationship. We contended that two antecedents of a productive relationship are identity and reputation. The ability to turn a healthy relationship into a profitable one is mediated by a third factor: fit. Fit involves whether the exchange partner has (or will have) something to sell that the other party wants to buy.

Indicators of identity: Willingness to share personal information or insistence on privacy. Privacy is the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others (Westin 1967). However, it comes at a cost: the ability to assert a particular identity, and with it title to the rights and privileges of that identity (Deighton 2003). Although academics have long recognized the importance of an individual's identity (e.g., Brown 1969; Tolman 1943), managers frequently overlook the relevance of an individual's social identity to his or her relationship with an organization. When a customer of a firm insists on privacy, it is not a costless or idle preference. It carries important information about the value of the relationship. It is a signal that identity is worthless in this relationship, or worse, that it might expose the customer to harm. Vulnerability in the context of this relationship is not tolerable.

Insistence on privacy, and by contrast willingness to share information and the degree of sensitivity of this information, therefore become potential leading indicators of the openness of the customer to relational exchange, and of what the customer hopes for from the relationship.

Indicators of reputation: Trust and brand strength. Another group of leading indicators of what the customer hopes for from the relationship relate to corporate reputation (Brown and Dacin 1997). Trust, the willingness to rely on an exchange partner in whom one has confidence (Moorman, Deshpandé, and Zaltman 1993), is arguably the most important dimension of reputation for this purpose. Trust, however, is only established by evidence of trustworthy conduct, and such conduct may be hard to find in markets where firms care about their reputations. In the absence of grounds for trust, brand strength serves as a compensating indicator. Following the information economics argument (Nelson 1974), a firm that builds a prominent brand may be understood by customers to have pledged a bond to its own integrity. Unfortunately, there is little academic research on the link between trust and future behavior (cf. Verhoef, Franses, and Hoeksra 2002).

Indicators of fit or misfit. A customer that trusts a firm with personally sensitive information and holds the firm

in high repute may nevertheless have no need to do business with the firm. Mediating the relationship between these indicators of relationship strength and the firm's value to the customer must be some measure of product-customer fit, which Bolton, Lemon, and Verhoef (2006) defined as "the compatibility between customer and product that occurs when the product provides what the customer needs." Recent research investigating the nature of the relationship (or fit) of the customer and the brand has found that customers with different characteristics have different satisfaction thresholds and, therefore, different probabilities of repurchase (Mittal and Kamakura 2001).

This section has suggested forward indicators of the way the customer values the firm. The next discusses properties of headlight indicators of a firm's valuation of customers and their future value. The challenge of managing marketing by adaptive foresight is to enhance both valuations while narrowing the gap between them.

PROPERTIES OF HEADLIGHT INDICATORS

How can firms' develop adaptive foresight? A suitable system of metrics should be developed that can be used—throughout the firm—to guide resource allocation toward strategies that increase customer equity. Gupta and Lehmann (2005, pp. 110-15) recommended that the firm develop metrics for each element of a "profitability tree" based on sources of customer equity (i.e., acquisition, retention, margins). Alternative strategies can be analyzed by tracing their effects through the tree. They recommended that firms develop two sets of metrics to provide diagnostic information: customer-focused metrics, to assess value *to* the customer; and company-focused metrics, to assess the value *of* the customer (p. 132). They argued that, because not all customers are equally profitable, investments in customers should be based on their profit potential. Customers should be categorized by whether the firm can offer them value, as well as by whether the firm can capture value from them, especially if they are treated differentially. Ultimately, these strategies require the firm to develop marketing programs targeted at individual customers or segments that influence acquisition, retention, and margins (by improving their cost structure, stimulating cross-buying, and so forth), thereby maximizing customer equity.

Much more work must be done to develop a forward-looking system of metrics that predicts customer equity. However, Gupta and Lehmann's (2005) profitability tree provides a useful framework for thinking about adaptive foresight. Clearly, the firm requires a mechanism that links strategic and tactical-level metrics ultimately to customer equity. Different metrics will be required at different levels

of the organization and within functional areas, and they must be linked, so that they "roll up" to predict customer equity. At the same time, if we understand leading indicators, we can potentially incorporate uncertainty into our predictions.

THE ADAPTIVE FORESIGHT PROCESS

As we consider the process of developing customer-based future metrics, it is encouraging to look at models of strategic foresight from other fields of management. For example, Schwartz (1991) suggested an eight-step approach to scenario building. Similar models are emerging in the areas of strategy (e.g., Fink et al. 2005) and operations research (e.g., Surana et al. 2005). In this section of the article, we build upon the approaches suggested in these related domains and suggest a four-step process of adaptive foresight for understanding and identifying "customer futures." However, as Schwartz (1991, p. 9) remarked, "The end result [of scenario building], however, is not an accurate picture of tomorrow, but better decisions about the future."

Step 1: Developing Foresight Capability

The first step that is necessary in developing a customer adaptive foresight process is the development of a foresight capability within the firm. Recently, Fink et al. (2005) have suggested a "Future Scorecard" that lays out an approach for creating strategic foresight using what the authors call both internal and external scenarios. What is most interesting about this approach, and how it relates to the approach we are advocating in this article, is its explication of how firms need to change to be able to understand and to adapt in dynamic environments. Two key approaches must be grasped to see the need for such a future scorecard: (a) systems thinking and (b) future open thinking (p. 361). Firms must engage in systems thinking—understanding that the environment in which they operate is a complex dynamic system. To do this, they must engage in future-open thinking, being willing to "unlearn the idea that a single predictive future exists" (p. 361), and be able to hold the possibility of multiple futures simultaneously.

We outline three additional key steps in developing strategic foresight: generating alternative futures, identifying key levers to influence customers, and developing offerings that fit customers' futures. The ability to engage in this open and future-focused type of strategic thinking is at the heart of achieving the first step in the customer adaptive foresight process—developing foresight capability.

Step 2: Generating Alternative Futures

The second step in the process of developing a customer-based adaptive approach is to generate a set of potential customer futures. To do this, firms must determine how far into the future they want to project and also must engage in marketing research to understand and to develop the set of potential customer futures. For example, the firm could envision customer futures as “close” as 3 to 6 months out, or as “far” as 20 years in the future. In the strategy literature, these potential futures are typically generated through scenario techniques; and, as suggested by Fink et al. (2005), these techniques for identifying future strategies typically should include both externally-focused (customer- or market-based) scenarios and internally focused (resource-based) scenarios.

To understand what these potential futures might be for customers and customers, however, mere scenario building will not be sufficient. Alternative measures and approaches will be necessary. First, identifying customer metrics and perceptions that have such a future component, as discussed above, will be critical. Second, using techniques such as ethnographic interviews (McCracken 1988) or the ZMET (Zaltman Metaphor Elicitation Technique) approach (Zaltman and Higie 1993) may prove useful. Of course, it is important to recognize that customer may not know what they want, or may not be able to imagine what they may want in the future. For example, customers satisfied with a Sony Walkman might never imagine they would want an Apple iPod. Thus, examining customer futures that the customers themselves may not be able to envision is equally important.

At this point, it is also important to understand not only what customers will want in the future but also what the firm may be able to offer customers in the future. A successful adaptive foresight model will recognize that it is critical to have an ongoing fit between the firm’s value to the customer and the customer’s value to the firm. One interesting and current example of a firm’s attempt to understand the customer’s future is ING’s “Create a Vision” CD. This tool enables customers to envision their dream retirement and to understand what their financial needs might be to enable them to achieve this ideal future. By capturing customers’ perceptions of their ideal futures, firms may be able to gain additional insight into the future needs of customers.

Step 3: Identifying Key Levers to Influence Customers

Once customer potential futures are generated, firms can then utilize two distinct lenses to evaluate these futures: (a) what levers does the firm have at its disposal

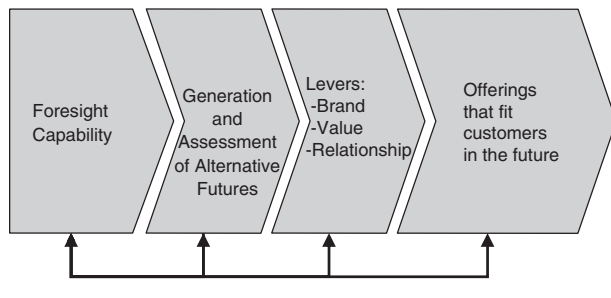
to influence customers in these future settings, and (b) can the firm use these (or other) levers to influence customer futures? In considering the levers or drivers that firms can use in these two distinct ways, one way to categorize the marketing actions that firms can take to influence customer behavior is to distinguish among brand, value and relationship drivers (Rust, Zeithaml, and Lemon 2000). Key marketing actions can be categorized into those that grow the brand (or brand equity), those that increase the value proposition (value equity) and those that improve customer relationships with the firm (relationship equity). Once customer potential futures have been identified, firms can examine the extent to which they are capable of influencing customers to do business with them (through brand-building, value-building, or relationship-building activities).

In addition, prior research suggests that firms can shape the environment and actually create opportunities (C. P. Zeithaml and Zeithaml 1984; V. A. Zeithaml, Varadarajan, and Zeithaml 1988). Recently, Kumar, Scheer, and Kotler (2000) have described this strategic orientation as “market driving” rather than “market driven.” In other words, a firm may be able to influence customers’ perceptions of the future through its own marketing actions. For example, mobile phone firms are currently introducing global positioning system (GPS) offerings on cell phones—although it is not clear that customers perceive a strong need for such software. Their advertisements often feature a fear or anticipated regret appeal, suggesting that customers, looking into the future, should consider the possibility that they may be in an emergency situation in which they would need to have GPS capability on their mobile phones.

Step 4: Developing Offerings That Fit Customers’ “Futures”

The most interesting possibility that arises out of the rich data collected on the ING “Create a Vision” CD mentioned earlier is the plethora of potential product and service offerings that ING might create based upon this information. As customers are asked to envision their futures, ING gains new understandings into what customers might need in the future. The fourth step in developing a customer adaptive foresight system is actually developing offerings that will fit these alternative customer futures. This approach, however, is quite risky, as it suggests that firms need to develop sets of offerings for each of the possible customer futures that may come to pass, not knowing which futures will actually occur. Thus, it will be important to incorporate theory-based approaches to account for the variability and uncertainty in future outcomes. Here, models from finance and option theory (e.g.,

FIGURE 1
Adaptive Foresight: The Process



Dixit and Pindyck 1995; Hogan et al. 2002) may be helpful in identifying the value and extent of uncertainty associated with each potential future and determining when it is most appropriate to invest resources in actually developing the offerings associated with each potential future.

An option value approach, for example, provides a quantifiable approach for the firm to determine when the uncertainty associated with a specific potential future has decreased sufficiently (though the identification of key leading indicators) to justify investing in marketing actions that are associated with the particular scenario. For example, if a set of scenarios examine the likelihood that consumers will be wearing wireless devices as fashion in the future, the presence of key signposts or leading indicators that suggest this scenario has a high probability of occurring reduces the uncertainty associated with this scenario. An option modeling approach can provide a decision rule to understand when investing in new products that will satisfy this emerging need will be a fruitful investment.

In summary, the development of a customer adaptive foresight process involves four steps (see Figure 1):

- Step 1: Developing foresight capability
- Step 2: Generating alternative futures
- Step 3: Identifying key levers to influence customers
- Step 4: Developing offerings that fit customers' "futures"

In considering how these four steps will work together to enable a firm to capture future customer metrics, it is important to note that this is an iterative and dynamic process, one that requires a perpetual "state of readiness" and flexibility on the part of the firm. To determine what it might actually take to move the levers (Step 3) to influence customer behavior, the firm will need to have in place the foresight capability (Step 1) to capture and assess information about customer futures (Step 2) and then the flexibility and capability to move the levers (Step 3) that will enable the firm to create and deliver offerings that fit the customer where he or she will be in

the future (Step 4). However, where the customer will be in the future will continue to change and to require updating, underscoring the need for the continuous feedback loops necessary in this process as noted in Figure 1.

Finally, as we consider the role of such an adaptive foresight capability, it is interesting to examine the extent to which this capability itself will influence customer behavior. For example, if a customer believes that a firm is continuously monitoring the future and identifying key trends, will this make the customer more likely, overall, to be loyal to the firm? Consider the recent advancements in airplane technology by both Airbus and Boeing. Although neither firm uses conventional CRM metrics, each firm is looking to the future of air travel and identifying potential "customer futures"—in this case the customers are both the airlines and the airline customers. Airbus believes that the airline customers will need larger aircraft to go from one big airport to another big airport (the new Airbus 380 can carry up to 555 passengers with a range of 8,000 nautical miles; see www.airbus.com). Alternatively, Boeing believes that airlines will need smaller, lightweight, fuel-efficient aircraft that can go "point-to-point" from many airports to many airports (the new Boeing 787 will carry on average 259 passengers, with a range of 3,500 nautical miles and using 20% less fuel; see www.boeing.com). It is feasible that the extent to which the airlines believe that these firms possess a strong capability to understand and adapt to the future may influence the airline companies' decisions of which manufacturer to purchase from and which aircraft to buy.

Similarly, customers may develop trust with product or service providers based upon their foresight capabilities—customers may tune to the Weather Channel to learn about an upcoming storm, believing that it has the best forecasting capability, or trust a specific customer electronics manufacturer when purchasing a product they plan to own for many years (e.g., a plasma television), recognizing that the product will need to be compatible with other devices that have not yet been developed. The potential relationship between the adaptive foresight capability and customer retention may suggest that a firm's ability to innovate (Subramaniam and Youndt in press) may actually be a driver of customer loyalty.

IMPLEMENTATION ISSUES

Even if relevant forward-looking measures for a company have been identified, there are a number of hurdles to be overcome for successful implementation. These tend to fall into three general categories: (a) managerial relevance, (b) situational and temporal influences, and (c) data quality and accessibility.

Managerial Relevance

Whereas there are a myriad of factors that determine business success, two critical issues are clarity of direction (Buckingham 2005) and process ownership (Kordupleski, Rust, and Zahorik 1993). Many forward-looking metrics are likely to represent higher-order attitudinal measures and therefore become less concrete to the workforce. As concepts appear more abstract/complex, it is more difficult for managers to provide clear direction to rally the organization under a single banner. Taken to the extreme, one might imagine quantum physics successfully predicting how customers will behave, but how could a manager inspire or direct his colleagues to act on this information?

Additionally, managers and employees typically do not have daily or even weekly access to customer attitudinal measures to guide them in their everyday performance. As a result, linking customers' attitudinal metrics with operational metrics that are regularly monitored by employees is critical to ensuring that changes to processes actually result in desired attitudinal outcomes by customers (Bolton and Drew 1994; Dean 2004; Deyong and Case 1998; Spencer and Crosby 1997). In this way, forward-looking metrics can be broken down into more tangible "actionable components." This produces additional managerial issues critical to success, particularly related to human resource management. For example, how will employee performance be measured relative to these operational metrics? Next, what incentive structure will be created to support performance on these measures? Furthermore, how will these metrics be monitored and modified to remain consistently linked to each relevant forward-looking metric?

Situational and Temporal Influences

As forward-looking measures are frequently likely to be higher-order attitudinal measures, the underlying causes of these attitudes are likely to differ by customers' particular circumstances and desires. For example, customer satisfaction has been shown to link with customers' share of wallet (SOW) (for example, Baumann, Burton, and Elliott 2005; Bowman and Narayandas 2004; Perkins-Munn et al. 2005). High satisfaction and high SOW, however, do not necessarily elicit behaviors desired by managers depending on the cause of this behavior. For example, if satisfaction and SOW are largely caused by poor pricing or cost management decisions, then these results come at the expense of a company's financial health (Keiningham et al. 2005).

Furthermore, customers' level of involvement in a product category has been shown to impact their behavioral loyalty to a brand (Van Trijp, Hoyer, and Inman 1996). Howard (1989) proposed three different levels of

decision making based upon the amount of active consideration that the customer invests in a particular purchase choice, strongly implying that metrics designed to predict customer behavior will vary in intensity by category (and therefore will not be universally applicable).

Time has also been shown to affect customers' perceptions and the relative impact of those perceptions on future customer behavior (Mittal, Kumar, and Tsiros 1999; Slotegraaf and Inman 2004). For example, Mittal, Katrichis, and Kumar (2001) reported that for an automotive firm, dealership service is twice as important in determining overall satisfaction as vehicle quality to new car buyers. When the same customers were surveyed 24 months later, however, analysis showed that vehicle quality was far more important than dealership service.

In some cases, time may be a correlate of experience. For example, Kekre, Krishnan, and Srinivasan (1995) found that among software users "usability" and "documentation" had higher weights for novices, but "capability" and "reliability" had higher importance among experts. Similarly, a number of other studies have shown that customer expertise can influence customer loyalty (Bell, Auh, and Smalley 2005; Maheswaran 1994; Mitchell and Dacin 1996). Experts were found to have more developed and complex cognitive structures compared with novices (Alba and Hutchinson 1987). As a result, experts may be more likely to be receptive to competitive offerings. Because novices will find it more difficult to make comparisons, they could perceive greater risk in decision making (Heilman, Bowman, and Wright 2000) and hence prefer to stay more loyal.

It is therefore reasonable to believe that time will impact the relative importance of various forward-looking metrics.

Data Quality and Accessibility

Perhaps the most daunting issues to successful implementation relate to the data (or lack thereof) itself. One of the most frequent problems is that of multicollinearity. Whether it be survey response bias, or multiple company activities affecting the customer at once, it is difficult to tease out precisely what is affecting customer behavior.

This problem is compounded when trying to transfer researcher findings to methods that can and will be acted upon by managers. With regard to multicollinearity, this is important because commercial and academic studies typically vary in their approach to and the importance of variability in attribute-level ratings of attitudinal data. Whereas managers are concerned with attribute-level variation as it relates to the derivation of attribute weights in an effort to determine the relative importance of potential issues for service improvement (Mittal, Ross, and

Baldasare 1998; Rust, Zahorik, and Keiningham 2000), academic studies typically strive to establish relationships between constructs with a high degree of internal validity.

Furthermore, if research regarding satisfaction and loyalty serve as a guide, derivation of importance for various forward-looking metrics is likely to be further hampered by asymmetry and nonlinearity in their relationship to customer behavior (Anderson and Mittal 2000; Austin and Singh 2005; Keiningham, Perkins-Munn, and Evans 2003). Therefore, managers may have additional difficulty deriving importance and establishing performance targets that correspond to thresholds that actually affect future customer behavior.

Even if multicollinearity, relative importance derivation, and proper target setting were not at issue, however, data quality and availability would still represent the most difficult hurdle to overcome for successful implementation by managers. Though computerized customer database systems are prevalent, rarely do firms have adequate information about their customers to effectively populate a customer database for purposes of effectively predicting customer behavior. The shortage, as discussed above, is a result of a number of issues: incompatible data sources, rapid data obsolescence, segregated attitudinal and behavioral data, and missing or uncollected data. In the latter case, even when data is somewhat uniform and integrated, the necessary components for calculating CLV or prioritizing relevant, right-time offers for customers is missing, or not in a useable format for analysis. Worse still, for most firms, conducting a census to collect relevant forward-looking metrics is not feasible or cost-effective. As a result, typically surrogates within the behavioral database must be used as proxies to fill in the vast amounts of missing data. Unfortunately, as might be expected, there is seldom a good fit with the data collected; if there were, this data would already be used to effectively predict future customer behavior (e.g., the forward-looking metrics would already exist within the customer data base).

The Best Is the Enemy of the Good

Despite the many obstacles to successful implementation, managers want and need better measures from which to anticipate the future. Whereas there will always be opportunities for improvement in the integration and implementation of these metrics within an organization, any guidance that these measures provide serves to enhance the probability of business success. Such measures serve as the headlights for managers on the journey down a dark and winding road—unable to light the entire path, but still enough to steer the vehicle safely home.

SUMMARY

In this article, we argue that customer metrics used by firms today largely report the past or present but that companies need to and can develop forward-looking customer metrics. We use the term *adaptive foresight* to capture the notion that companies can be positioned to predict the future by exploiting changes in the business environment and anticipating customer behavior. In this article, we began by reviewing the metrics that have been and are currently being used to capture customer focus. Next, we discussed possible “headlight” or forward-looking customer metrics that would allow firms to anticipate changes and provide opportunities to increase the value of the customer base. We then identified the conditions under which the new metrics would be appropriate and offered a process for developing adaptive foresight. Finally, we discussed the implications of adaptive foresight for successful customer asset management that increases long-run business performance. In the words of E. L. Doctorow, “You can only see as far as your headlights shine, but you can make your journey that way.”

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