Marketing Actions and the Value of Customer Assets

A Framework for Customer Asset Management

Paul D. Berger
Boston University

Ruth N. Bolton
Vanderbilt University

Douglas Bowman
Emory University

Elten Briggs
University of Oklahoma

V. Kumar
University of Connecticut

A. Parasuraman
University of Miami

Creed Terry
Vector Marketing Corporation

This article develops a framework for assessing how marketing actions affect customers' lifetime value to the firm. The framework is organized around four critical actions that firms must take to effectively manage the asset value of the customer base: database creation, market segmentation, forecasting customer purchase behavior, and resource allocation. In this framework, customer lifetime value is treated as a dynamic construct, that is, it influences the eventual allocation of marketing resources but is also influenced by that allocation. By viewing customers as assets and systematically managing these assets, a firm can identify the most appropriate marketing actions to acquire, maintain, and enhance customer assets and thereby maximize financial returns. The article discusses in detail how to assess customer lifetime value and manage customers as assets. Then, it identifies key research chal-

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lenges in studying customer asset management and the managerial challenges associated with implementing effective customer asset management practices.

Marketing managers must grapple with complex cross-functional, cross-border, and cross-disciplinary issues to understand how firms relate to their markets (Kinnear 1999). These issues are particularly complex when a firm assesses the effect of marketing actions on the long-term value of the customer base. What expenditure will have more impact on the value of a firm's customer base: a new advertising campaign or improvements in service quality? Training for personnel or an investment in technology? How do the elements of a coordinated marketing strategy influence the purchase behavior of different market segments over time, and how will this affect the firm's revenue streams? What are the differential effects of changes in pricing structure on customer acquisition, retention, and cross-buying? How do marketing and operations elements interact to grow or diminish customer value?

The term *customer value* can be a source of ambiguity because it has been defined in the marketing literature in at least two different ways (cf. Parasuraman 1997; Woodruff 1997). In this article, customer value is conceptualized as the "value that the customer provides to the firm" instead of the "value provided by the firm to the customer" (Roberts 2000). The latter description is derived from traditional microeconomic theory and is equal to the difference between the customer's *reservation price* (i.e., the maximum amount the consumer would be willing to pay for the product) and the actual *market price* (i.e., the amount for which the firm sells the product). This literature on customer value conceptualizes the construct as *customer perceived value*, that is, customers' perceptions of the benefits they receive from a firm relative to what they give up in the form of monetary and nonmonetary costs.

In contrast, our focus herein is on *asset value of customers* from a firm's standpoint, that is, customers' lifetime value to the firm. As such, throughout this article, the customer value construct represents the asset value of the customer. The value the customer provides to the firm is the sum of the discounted net contribution margins over time of the customer, that is, the revenue provided to the firm less the firm's cost associated with maintaining a relationship with the customer (Berger and Nasr 1998). In other words, the customer is an entity (organization, household, or individual consumer) that provides the firm with a stream of revenue (and costs) and therefore becomes an integral component in the tabulation of a firm's overall net worth. Based on this characterization of customer value, the customer can be viewed as an asset to the firm. The firm cannot perfectly predict how much an individual customer will contribute to its net worth, but it can calculate the expected value of the cash flows associated with an individual customer based on the customer's characteristics and the firm's planned marketing actions.

The notion that marketing mix variables can influence the value of a firm's customer base entails incorporating concepts from environmental management into marketing. Whereas traditional marketing theory places the firm in an adaptive position regarding the opportunities that it encounters in the environment, environmental management "argues that marketing strategies can be implemented to change the context in which the organization operates" (Zeithaml and Zeithaml 1984). It is a proactive perspective that focuses on the acquisition of potentially valuable customers and the maintenance and enhancement of the customer-firm relationship (Berry 1983). For example, Jaworski, Kohli, and Sahay (2000) discussed some modern methods a business can undertake to proactively construct its own markets. With technological advancements, firms are becoming increasingly capable of managing their customer base to shape the environment in which they operate (Roberts 2000). Consequently, firms have begun to compare the long-term profitability of standardizing marketing strategies across customers with the long-term profitability of customizing marketing strategies to market segments. To make these strategic decisions, firms must accurately access the value of each segment or individual customer.

This article examines how marketing actions influence the value of the customer for the duration of the customer-firm relationship or customer's *lifetime* (e.g., Reinartz and Kumar 2000) rather than examining how marketing actions influence customer value at some static point in time. We use the term *customer lifetime value* (CLV) to refer to the monetary value of the customer (or group of customers) during this time period. Empirical research has encountered numerous problems in understanding how marketing expenditures or investments are related to customer value and profitability (cf. Anderson and Mittal 2000). Indeed, there are so many challenges in linking marketing actions to CLV that some managers and researchers have concluded that marketing actions are ineffective in increasing the value of the customer base. For example, research by Kearney and Little reported that 80% of more than 100 British firms did not see a significant impact as the result of their total quality management efforts and that approximately two thirds of the 500 U.S. firms did not realize any competitive gains ("The Cracks in Quality" 1992). Such findings have heightened the need for better ways to assess how marketing actions influence CLV.

In early approaches to customer asset management, marketing managers and researchers focused on relating marketing actions to intermediate outcomes—that is, to marketing metrics such as survey-based measures of customer satisfaction/quality or customer retention—and thereby to financial measures of profitability. This approach typically entailed statistical analyses of aggregated data for a cross section of firms or organizational units (e.g., Anderson, Fornell, and Lehmann 1994; Anderson and Sullivan 1993; Roth and Jackson 1995). Despite some success (e.g., Capon, Farley, and Hoenig 1990), there are several technical challenges to relating marketing metrics to profitability in this fashion. First, marketing metrics are frequently highly skewed (e.g., Bowman and Narayandas 2001; Mulhern 1999). For example, in industrial markets, it is not uncommon to see more than 80% of a customer base reporting some degree of satisfaction (e.g., Bradlow and Zaslavsky 1999) or the majority of a vendor's customers awarding it 50% or more of their purchases (e.g., Wind 1970). Second, the relationship between customer satisfaction, retention, and profitability is typically nonlinear and asymetrical (e.g., Anderson and Mittal 2000). Statistical analyses that assume a linear relationship (e.g., correlations) may mask the complexities of the underlying linkages. Third, relationships outside the focal vendor-customer relationship may create moderating or mediating effects. For example, failure to account for the competitive environment or relationships with a collaborator may result in a model that is conceptually underspecified (Bolton and Drew 1994). Last, there are a variety of model, measurement, and sampling errors that confound or obscure empirical findings based on aggregate statistical analyses (cf. Szymanski, Bharadwaj, and Varadarajan 1993).

The complexity of these issues implies that customer asset management guidelines cannot be derived from statistical relationships between measures based on highly aggregated, cross-sectional data. Instead, CLV analyses require each firm to make a careful assessment of the costs and benefits of alternative expenditures and investments and then determine the optimal allocation of resources to homogeneous customer groups. Recently, researchers have developed much more detailed conceptualizations of how customer acquisition, retention, and add-on selling drive "customer equity" or the value of the customer base (Berger and Nasr-Bechwati 2001; Blattberg and Deighton 1996; Blattberg, Getz, and Thomas 2001; Bolton, Lemon, and Bramlett 2001; Rust, Zeithaml, and Lemon 2000). This article advances these ongoing efforts by developing a framework for customer asset management that is organized around four critical and interrelated actions that firms must take to understand how their marketing actions affect the value of their customer assets.

A noteworthy feature of our framework is that it treats CLV as a *dynamic* construct—one that not only influences the eventual allocation of marketing resources but also is influenced by that allocation. It should thus be viewed as an endogenous variable that fluctuates with the marketing actions of the firm. In other words, changes in the value of customer assets (triggered by changes in marketing and hence customer actions) and changes in the allocation of firm resources (leading to changes in marketing actions) occur in a continuous, cyclical fashion.

In our view, the four actions that firms must take to understand how their marketing activities affect the value of their customer assets are the following:

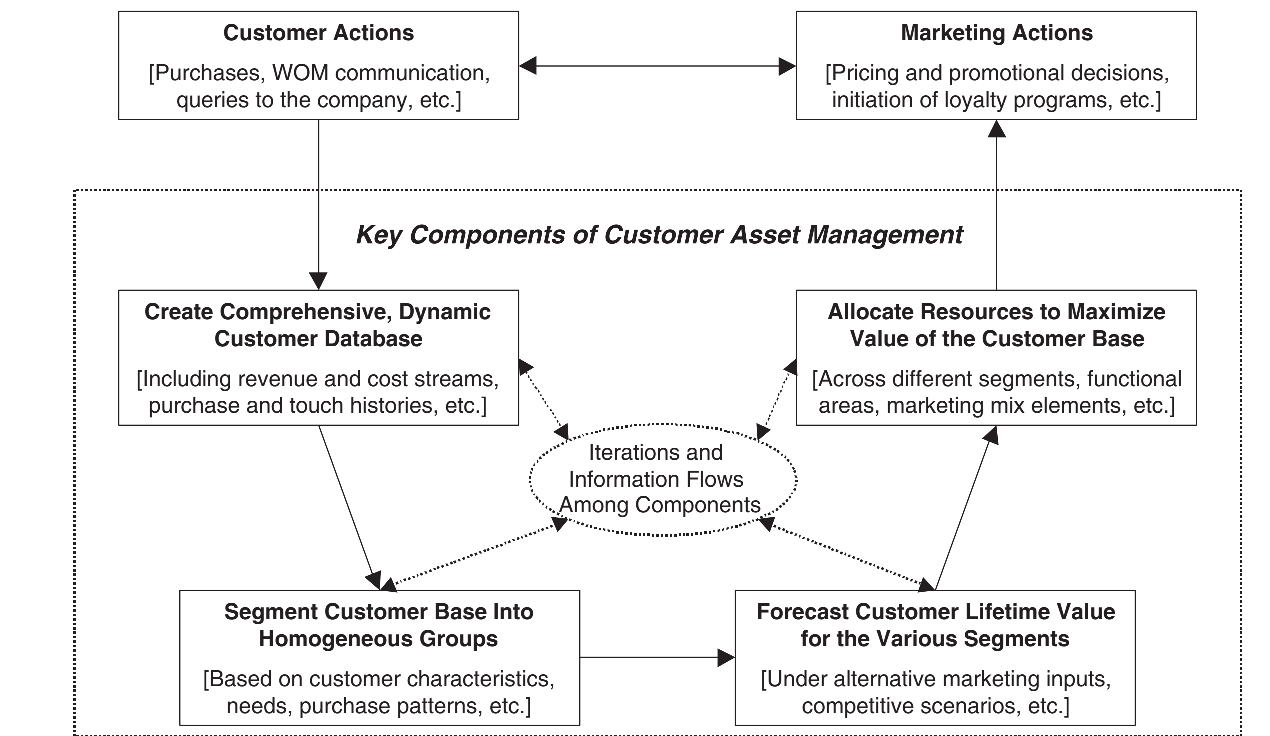
1. create a database guided by marketing intelligence for the calculation of CLV,
2. segment according to customer needs and purchase patterns,
3. forecast CLV under alternative scenarios, and
4. allocate resources to maximize the value of the customer base.

Figure 1 depicts these actions as part of an overall framework for managing customers as assets. The top portion of the figure reflects the fact that a firm's marketing actions can influence customer actions and the latter, in turn, can influence the former. The thesis of our article is that by viewing customers as assets and systematically managing those assets through the sequence of steps shown in the boxed area of Figure 1, a firm will be able allocate its resources optimally and take the most appropriate marketing actions to acquire and maintain those assets so as to maximize the returns from them. It is also important to note that although the four components of customer asset management in the boxed area of Figure 1 generally follow a step-by-step, counter-clockwise sequence, in reality these are not totally independent steps. As shown by the oval at the center of the boxed area, the steps are intertwined and dynamically linked. Thus, our model reflects potential simultaneities such as forecasts of CLV not only influencing but also being influenced by a firm's marketing strategies. In the remainder of this article, we first discuss in detail the four components of managing customers as assets, and we then discuss the research and managerial implications of our framework.

CREATE A DATABASE GUIDED BY MARKETING INTELLIGENCE

This section describes the nature of the data that link a firm's marketing actions to CLV and discusses the creation and management of a useful database. At the heart of any

FIGURE 1
A Framework for Managing Customers as Assets



of the CLV models is an assessment of (1) how much revenue a firm gains from the relationship with an individual customer and (2) the cost to maintaining the relationship with the customer (Berger and Nasr 1998). Hence, the first step is to develop a comprehensive database that describes the stream of cash flows associated with individual customers—arising from the customer purchase history and the marketing actions of the firm—as well as a "touch history" that records the customer experiences.

Revenue and Cost Streams Associated With Individual Customers

Capturing the revenues and costs for each customer goes beyond recording the history of customers' individual purchase transactions. In direct marketing contexts, firms are able to assign the costs of direct communication, delivery of the product, and promotions to individual customers (Berger and Nasr-Bechwati 2001; Dwyer 1989; Keane and Wang 1995). In more traditional businesses, firms must create methods for accurately attributing the indirect costs of marketing actions to individual customers or customer segments. For example, Niraj, Gupta, and Narasimhan (2001) highlighted the importance of logistics-related costs in the lifetime value calculation and introduced activity-based costing as a method to accurately identify the relevant costs. Cost allocation can be particularly challenging for firms in industries such as telecommunications, computing services, biotech, and financial services—where marketing activities might include programmatic efforts, such as service improvement efforts or investments in physical infrastructure, as well as direct marketing communications.

Capture Touch History and Purchase History

A customer's purchase history conveys the monetary value of transactions, but a "touch" history provides information about the customer's activities between transactions and (consequently) the probability of repeat purchases, cross-buying, or recommendations to others. By touch history, we mean any contact that the customer has with the firm. With the advent of electronic commerce, most firms use a variety of channels, for example, Charles Schwab Corporation has many ways of touching the consumer that vary by market segment (Brady 2000). These are activity-based interactions that can be customer initiated or firm initiated (e.g., Bowman and Narayandas 2001). Touches are not normally considered in reach, frequency, and monetary (RFM) value models that predict whether an individual customer is "due" to purchase (i.e., an alive and active customer of the firm) or "dead" (i.e., a customer who has ended his relationship with the firm) (Allenby, Leone, and Jen 1999; Schmittlein, Morrison, and Colombo 1987). However, this factor can take on great significance in some industry contexts, for example, for continuously provided services (financial, telecommunications, etc.) and durables when the typical purchase cycle of a business is extremely long. For example, Bolton (1998) found that customer- and firm-initiated contacts significantly influence the duration of the customer-firm relationship for wireless telephone customers and that this change in customer lifetimes substantially influences the firm's revenue stream. Because touches influence customer behavior and thereby revenues (as well as costs), customer touch histories are important in the prediction of customer profitability in future business cycles.

Beyond recording the number of customer touches, the nature or significance of the touch should also be recorded by the firm (Roberts and Berger 1999). Customer-initiated touches are equally, if not more, important than firm-initiated touches because the customer indicates some interest in the firm by this act and customer effort reduces the marketing costs of the firm. The performance of the vendor during these touches will have an impact on customer share of category requirement and word-of-mouth behavior (Bowman and Narayandas 2001). Furthermore, different types of touches—such as a customer inquiry about a bill or regarding new products, a firm-initiated direct marketing contact or a service call—will have different effects on customer behavior and revenue streams. Finally, many firms recognize the importance of "extreme" incidents—when the customer has either been highly satisfied or dissatisfied. These incidents can have a significant and substantial effect on customer lifetimes and revenue streams (e.g., Bolton, Lemon, and Bramlett 2001).

Qualitative Considerations

Some firms, such as Sears, have implemented customer relationship management (CRM) systems that collect and analyze customer responses to marketing efforts and then link them to consumer behaviors and financial indicators (Heskett et al. 1994; Rucci, Kirn and Quinn 1998). However, it is important to recognize that even the most comprehensive database is unlikely to capture all the benefits of marketing actions. Some benefits, such as positive word of mouth or the ability to attract new or former customers, are difficult to quantify (Danaher and Rust 1996; Zeithaml 2000). Researchers are only beginning to analyze and quantify the benefits of word-of-mouth behavior (e.g., Anderson 1998; Dick and Basu 1994; Hogan, Lemon, and Libai 2001.)

Database Management

As technological advances have facilitated electronic commerce and data-gathering methods, the amount and variety of information that firms can assemble have increased and will continue to do so. These advances should enable a firm to better understand the experiences of its customers and thereby provide greater insight into the effect of marketing actions on its customers. Although this potential exists, the actual organization and implementation of information into a usable database to calculate CLV have been a challenge for many firms. For example, firms have faced substantial obstacles to integrating data "silos" that typically segregate purchase records, direct marketing information, operations and customer service records, account management, and billing records. These obstacles are even greater when a firm has legacy systems for information storage or different and incompatible systems arising from merger and acquisition activity. The information in the database must be organized properly to drive CLV calculations. We list some of the most important, and frequently encountered, problems below.

Determining the appropriate unit of analysis. The most fundamental question is, Who is the customer? This specification of the correct customer unit will define the scope within which the profitability analysis is conducted (Mulhern 1999). In a business-to-business context, firms must investigate whether different organizational units (or geographic locations) of the same firm should be considered different customers. The answer may be "yes" if the units make independent purchase decisions and "no" if decision making is centralized. Furthermore, the firm may interact with or "touch" a number of different individuals within a customer organization in connection with a single purchase. For example, the firm may interact with a purchasing manager and multiple end users, as well as the decision maker or decision-making group. As such, the definition of the unit of analysis needs to incorporate this complexity to accurately capture all revenues, costs, and "touches" associated with presale, during-sale, and postsale contacts with the customer unit. In a consumer context, the firm must investigate whether the individual, the husband and wife couple, or the household is a customer for the purposes of CLV. The answer may be "an individual" for some financial services (e.g., a credit card) but "a couple" for other services (e.g., a mortgage). The correct definition of a customer requires a careful analysis of the buying process so that the definition can be applied systematically in the collection and integration of customer information.

Establishing the time horizon for CLV calculations. Certain marketing actions—such as investments in technology and human resources—pay off over a longer time frame than a single purchase cycle. Therefore, a comprehensive CLV analysis must consider a long-term time frame. But how long? Often, the time horizon is determined by data availability, but this constraint is diminishing as time passes. More important, firms with many products must recognize that their products may have dramatically different purchase cycles so that the time horizon should encompass the longest relevant cycle. This issue becomes important when the firm's CLV analysis considers cross-buying or add-on purchases. Recently, researchers have recognized that "100% share of customer" may not be an appropriate measure of customer loyalty (Dowling and Uncles 1997). Instead, it may be more appropriate to model switching behavior, that is, how customers allocate their purchases between the firm and its competitors over time within a category (Rust, Zeithaml, and Lemon 2000).

Merging and cleaning data. Customer information is typically entered into databases by a variety of employees, including account representatives, frontline customer service representatives, operations personnel, and so forth. Often, there are data that are missing, incomplete, or in error for a variety of reasons. For example, firms may have poor or nonexistent specifications for record keeping, database entry is a lower priority than other organizational objectives (such as serving customers), employee turnover and human fallibility lead to entry errors, and so forth. Furthermore, some firms mistakenly organize their records by year or geographic location, rather than by customer. Other firms do not have a common customer identification number to match records from different information systems. Procedures must be devised to match and merge customer information from different systems.

SEGMENT ACCORDING TO CUSTOMER NEEDS AND PURCHASE PATTERNS

The preceding discussion may seem to imply that there are too many imponderables to accurately calculate CLV for individual customers. Certainly, firms that have little or no historical information about customers, such as firms operating in consumer mass markets, may have to resort to customized market research to calculate CLV for a sample of customers. The nature of the industry and the market dramatically influences firms' ability to calculate CLV in consumer markets. Early applications of CLV analysis have (generally) occurred in markets in which customer-firm relationships are longer and purchase and touch histories are available (albeit collected for operational or financial reasons). Consumer applications include continuously provided services such as financial, telecommunications, information, airline, and hospitality services (cf. Rust, Zahorik, and Keiningham 1994) or direct marketing firms such as in newspaper publishing and insurance companies (Dwyer 1989; Keane and Wang 1995). However, calculations of CLV for individual customers are more often feasible in business-to-business markets because (generally) the size of the customer base is smaller and customer information is more extensive. For example, Niraj, Gupta, and Narasimhan (2001) calculated the profitability of each of 658 individual industrial customers for a selected distributor.

The Rationale for Market Segmentation

In many instances, the firm simply has too many customers to individually target them all and apply "one-to-one" relationship marketing principles (cf. Peppers and Rogers 1999). Instead, they segment their customers into reasonably homogeneous groups and calculate average CLV measures. In our remaining discussion, we will consider the situation in which the firm segments its customers, recognizing that the segment may be an individual customer. In this type of analysis, when we say, for example, that about 400 of 1,000 new customers in a given segment will purchase again in the next 2 years, we do not know which individual customers will purchase again, and we do not need to know this information. Instead, we can build market response functions for customer segments and forecast customer segment behaviors and lifetime values from these functions. Our predictions are a probability distribution of possible outcomes for each customer based on (a) the individual customer's characteristics, (b) the segment/group's response function, and (c) assumptions about the marketing actions of the firm and its competitive environment. Thus, the criticism that there is great uncertainty about an individual customer's future and that (consequently) CLV is not useful is totally misplaced.

Market Segmentation Methods

Differences between customers' lifetime values can be attributed to their distinctive purchase patterns.[1] Assuming

1. The firm's predictions of its customers' lifetime values may influence its behavior toward them, thereby influencing purchase patterns. Hence, it might be useful to segment first by (probably crude) measures of lifetime value and then by customer needs and purchase patterns.

that appropriate segmentation tools are available, the goal is to identify individual customers who desire similar benefits and exhibit similar behaviors and thereby form (relatively) homogeneous segments such that there is heterogeneity across segments (Wedel and Kamakura 1999). A convenient market segmentation heuristic in firms that organize customer records by year and month is to group customers by the date they made their first purchase. Unfortunately, assigning customers to segments in this way usually does not provide enough homogeneity within the segments and heterogeneity between the segments to be useful in assessing CLV. Instead, market segmentation methods should be based on customers' needs and purchase behavior, taking into account such factors as their purchasing power, their purchasing regularity, and the type of products that they purchase.

Market segmentation requires a careful analysis of customer needs and behavior patterns. For example, technological readiness (TR) is an inherent trait that affects consumers' willingness to try new developments in technology or innovations (Parasuraman 2000). It has four facets: innovativeness or the tendency to try new things, optimism or the general feeling that technology is a good thing, insecurity or fear of technology, and discomfort or an overall feeling of paranoia. If TR is positively correlated with adoption rates for high-technology products, a firm offering such products could segment customers by levels of TR. There is evidence suggesting that distinct customer segments with differing TR profiles exist (Parasuraman and Colby 2001). Also the TR-based segments differ significantly in terms of (a) time of adoption and frequency of usage of technology products (which could affect purchase histories and revenue streams) and (b) the nature and types of aftersales support they might need (which could affect touch histories and cost streams). Thus, the identification of segmentation variables associated with specific purchase and touch patterns will ultimately help firms to target and acquire the "right" customers, as well as spend retention dollars wisely, to maximize the value of the customer base (e.g., Blattberg and Deighton 1996).

Segment Response Functions

Much research to date has focused on the maximization of antecedents of customer-perceived value such as customer satisfaction or customer loyalty (Reichheld 1996). If we believe that a solid base of marketing knowledge exists about the antecedents of customer behavior, then it is useful to consider customer-perceived value and/or customer profitability as the goal or objective of interest and customer purchase behavior as the focal variable to be explained or predicted. This approach implies that, after segmenting customers by their purchase patterns, the firm must estimate response functions that describe how individual customers' purchase behavior depends on marketing actions. Statistical models for different market segments provide measures of individual customers' response to various marketing and operation activities that the firm might undertake.

The majority of extant studies have focused on statistical models of purchase behavior without necessarily linking them to CLV metrics. Most commonly, researchers have estimated a dynamic model that provides probabilities that a customer is alive (i.e., an active customer of the firm) at a given time period during the business decision cycle (Allenby, Leone, and Jen 1999; Rust and Zahorik 1993; Schmittlein, Morrison, and Colombo 1987; Schmittlein and Peterson 1994). The statistical issues associated with estimating these models are nontrivial. For example, Thomas (2001) recently described how to model customer lifetimes prior to acquisition by accounting for the absence of information about nonacquired prospective customers using a Tobit model with selection. If the marketing actions that influence lifetimes are identified, then managers can monitor purchase behavior and manipulate marketing actions to increase the lifetime of these individual customers and consequently the value of the customer base. However, since strength of relationship—not just the length of the relationship—matters (Reinartz and Kumar 2000), firms must consider multiple aspects of purchase behavior, not just retention probabilities. Consequently, researchers have begun to model other purchase behaviors, such as cross-selling (e.g., Kamakura, Ramaswami, and Srivastava 1991) and word-of-mouth behavior (e.g., Anderson 1998; Hogan, Lemon, and Libai 2001).

FORECAST CUSTOMER LIFETIME VALUE UNDER ALTERNATIVE SCENARIOS

The core of any CLV forecast is a financial model that integrates the revenues and costs associated with a firm-customer relationship over time. The revenue and cost forecasts are developed from separate statistical submodels. Each component of the financial model is a forecast conditional on assumptions about the firm's marketing actions, competitor actions, and environmental conditions. This section describes alternative forecasting approaches and their critical features.

Linking Statistical Submodels to Financial Outcomes

Researchers have built statistical models of how marketing effort influences customer purchase behavior and linked them to customer value or profitability. For example, Keane and Wang (1995) used such an approach in modeling CLV in the newspaper publishing industry. Such statistical models of customer purchase behavior can provide important insights into how the firm should manage its customer assets. Furthermore, if separate response functions have been estimated for each segment, then marketing actions can be targeted to specific segments or individual customers.

There are numerous statistical issues relevant to the development of models that describe how marketing effort influences customer purchase behavior for a given segment and how models of purchase behavior can be incorporated into CLV metrics (Bolton, Lemon, and Verhoef 2001; Rust, Zeithaml, and Lemon 2000). Foremost, it is important to recognize that CLV is driven by the strength of the customer-firm relationship as well as its length. For example, it is possible for a consumer who purchases many or high-margin products/services to be less valuable if his or her lifetime is very short, when compared with a consumer whose purchases few or low-margin products/services but maintains a long relationship with the firm. This scenario is even more likely when we consider that the profitability of a consumer or business customer normally increases the more time he or she spends with the firm (cf. Kalwani and Narayandas 1995; Reichheld and Sasser 1990).

Statistical Models of Purchase Behavior

Marketing scientists have modeled many dimensions of customer purchase behavior, including the customers' first purchases (e.g., Thomas 2001), retention (e.g., Rust and Zahorik 1993) or the duration of the customer-firm relationship (e.g., Bolton 1998), the usage levels of services (Bolton and Lemon 1999), and cross-buying of additional products and services (e.g., Schmittlein and Peterson 1994; Verhoef, Franses, and Hoekstra 2001), as well as word-of-mouth behavior (e.g., Hogan, Lemon, and Libai 2001). See Table 1. To date, there are a relatively small number of studies that have examined only a few marketing actions (i.e., direct marketing, loyalty programs, price, service levels). However, these efforts have demonstrated that statistical models of purchase behavior over time will typically require flexible, nonlinear functions. They must also capture heterogeneity in customers, including the moderating effects of individual customer characteristics (e.g., Mittal and Kamakura 2001). It is also important that response function parameters be allowed to vary over time (e.g., Heilman, Bowman, and Wright 2000; Mittal, Ross, and Baldasare 1998).

Often, to ensure that the modeling effort captures the relationships between purchase and various independent/input variables, one uses a set of categorical variables to represent [even] continuous variables, such as time since last purchase, age, and others. Indeed, the purpose of this treatment is to *not* have to presuppose/assume *any* functional form, be it linear (which is what is assumed most of the time) or nonlinear. For example, time since last purchase might be modeled as 4 (0,1) categorical variables, X1 to X4, representing five categories. For example, X1 = 1 if time since last purchase is less than 1 month, 0 otherwise; X2 = 1 if time since last purchase is between 1 month and 3 months, 0 otherwise; X3 = 1 indicating 3 to 6 months; and X4 = 1 indicating 6 months to a year. The final category, more than a year, is "the dummy" category and left out and thus becomes part of the intercept. These issues are discussed and implemented in, for example, Berger and Magliozzi (1992) and Lix, Berger, and Magliozzi (1995).

Channel Harmony

Customer acquisition contributes to short-term revenue and profit targets. Building repeat purchases requires a customer experience that is rational and emotional, as well as informational and tangible in its benefits. To increase long-term CLV, firms must create an experience that focuses on well-defined customer needs, thereby maintaining and enhancing relationships with individual customers. One consideration in the allocation of resources to marketing actions to create and enhance relationships is *channel harmony*. We define channel harmony as the degree to which the firm distributes its products and contacts to its customers through channels and communication vehicles that are synchronized and complementary. Developments in the new economy have prompted firms to contact customers via multiple channels, including electronic channels. These developments have sparked a critical and immediate need to identify the levels of marketing expenditures for each channel (given expected revenues from customers) that will provide firms with maximal opportunities for customer acquisition, retention, and cross-selling. Thus, when a firm achieves a high degree of channel harmony, its alternative channels will complement one another and have a positive effect on the value of a firm's customer base. However, low degrees of channel harmony indicate that the allocation of the marketing resources is not efficient. To identify optimal resource allocations within and across channels, sales response functions must capture differences in efficiency across various channels and the potential benefits of synchronizing communications to customers across these channels.

TABLE 1
Selected Longitudinal Models of Customer Purchase-Related Variables

Study	*Focus of Study*	*Context*	*Data and Modeling Framework*
Acquisition			
Thomas (2001)	Link acquisition with retention	Services: group membership	Database; latent class tobit
Berger and Nasr-Bechwati (2001)	Link promotional budget to acquisition and retention	Various	Illustrative examples only
Retention			
Bolton, Lemon, and Bramlett (2001)	Link service operations with retention	Service: industrial high tech	Database; logistic regression with mixed effects
Rust and Zahorik (1993)	Link satisfaction and retention	Service: retail banking	Survey; logit
Relationship duration			
Allenby, Leone, and Jen (1999)	Interpurchase times	Services: brokerage trading	Panel data; Generalized gamma
Bolton (1998)	Duration with a vendor	Services: cellular telephone	Quasi-panel; proportional hazards regression
Reinartz and Kumar (2000)	Link duration and profitability	Retailer: catalog selling	Database; negative binomial distribution (NBD)/ Pareto
Schmittlein, Morrison, and Columbo (1987)	Counting customers	Various	Illustrative examples; NBD/Pareto
Schmittlein and Peterson (1994)	Customer base analysis	Industrial: office products	Database; NBD/Pareto
Profitability and duration			
Niraj, Gupta, and Narasimhan (2001)	Link characteristics to customer profitability	Channels: grocery store distributor	Database; stochastic model
Reinartz and Kumar (2000)	Link customer relationship management (CRM) characteristics to customer profitability	Retailer: catalog selling Industrial: high-tech	Database; NBD/Pareto Proportional Hazard regression
Venkatesan and Kumar (2001)	Optimal allocation of resources to maximize customer profitability	Industrial: high tech	Database; generalized gamma; genetic algorithms
Product purchase/service usage			
Bolton and Lemon (1999)	Service usage intensity over time	Services: Interactive TV, cellular	Panel data (2 observations); Tobit
Keane and Wang (1995)	Create customer lifetime value (CLV) model for an industry	Services: newspaper publishing	Illustrative examples only
Gonul and Srinivasan (1996)	Coupon expectation and customer purchase behavior	Retail: disposable diapers	Panel data; stochastic model
Cross-buying			
Kamakura, Ramaswami, and Srivastava (1991)	Order of product acquisition	Services: consumer financial	Diary panel; latent trait analysis
Verhoef, Franses, and Hoekstra (2001)	Cross-buying	Service: consumer financial	Survey and database; ordered probit
Word of mouth			
Bowman and Narayandas (2001)	Word-of-mouth incidence, quantity	Manufacturers: customer-initiated contacts	Survey; logit, NBD regression
Dick and Basu (1994)	Conceptual framework	None	None
Hogan, Lemon, and Libai (2001)	Word-of-mouth influence on profitability	Consumers: hairstyle services	Survey (different tenures); subsample measures
Share of customer purchases			
Bowman and Narayandas (2001)	Share of purchase over time	Manufacturers: customer-initiated contacts	Survey; iterated weighted least squares
Rust, Zeithaml, and Lemon (2000)	Customer equity	Products and services	Survey; lifetime value
Brand choice			
Heilman, Bowman, and Wright (2000)	Brand preference evolution	First-time parents; baby products	Panel data; latent class logit
Erdem and Keane (1996)	Brand choice processes	Retail: laundry detergent	Panel data; maximum likelihood

We illustrate the complexities of creating channel harmony by describing Cutco® Cutlery Corporation, a manufacturer of high-end kitchen cutlery and other accessories. Its primary distribution outlet is through independent contractors (mainly college students) who perform in-home demonstrations of the products for clients with which they personally schedule appointments. The in-home demonstration acts primarily as a customer acquisition initiative, and follow-up activity is limited (due to the significant turnover among the sales personnel). Consequently, Cutco® also directly markets its products via an annual spring and fall catalog, which provides the firm with an additional revenue stream from its customers beyond their initial purchase. To offer its existing customers additional ordering flexibility, the firm has made investments in online ordering systems and has increased its presence at fairs and trade shows. Cutco® considers integrating the value of the initial in-home customer acquisitions with the value gained from repeat purchases through these multiple channels as its major challenge. A critical component to the effectiveness of its CLV management is maintaining a balance between the earning opportunity of the independent sales organization and the customer convenience, service, and value provided at all the additional "touch points." Cutco's multiple channels provide a greater means for customer-initiated communications. Bowman and Naryandas (2001) found that customers who initiate contact with the manufacturer are typically highly loyal.

ALLOCATE RESOURCES TO MAXIMIZE THE VALUE OF THE CUSTOMER BASE

Customer asset management requires that firms make a careful assessment of the costs and benefits of alternative expenditures and/or investments and identify the optimal allocation of resources to marketing actions directed at market segments or individual customers over time. By comparing the value of the customer base derived from forecasts under different marketing decision alternatives, it is possible to identify "better" (if not optimal) ways to allocate resources to different marketing actions. This comparison process should take place within a comprehensive decision model that characterizes the goals or objective function of the firm.

Simplified linkages between statistical models of purchase behavior and the firm's objective function will provide unrealistic and suboptimal resource allocation decisions. For example, assuming a linear relationship between customer lifetimes and profitability has been shown to be invalid in a noncontractual business-to-consumer setting (Reinartz and Kumar 2000). A linear association between customer lifetimes and profitability would suggest allocating all the marketing resources to longer lifetime customers (a corner solution in mathematical terms), and it would not identify the optimal allocation of resources between prospective customers and existing customers. In some instances, both long- and short-life customers can be profitable. The question then is to determine how to allocate resources across customers, focusing more resources on more profitable customers.

Decision Support Models

Managers need decision support models that relate costly firm inputs to customer purchase behavior and forecast the value of the customer base. By using these models to forecast the future value of the customer base under alternative scenarios, firms can increase lifetime revenues and reduce costs by allocating existing marketing dollars more efficiently and effectively. Furthermore, by considering alternative environments and alternative marketing actions, the firm can identify new initiatives that can increase the value of the customer base (Seybold 2001). Consequently, decision support models enable firms to evaluate diverse and large-scale investments in marketing actions, operations, technology, and human resources, using a common metric. Recently, marketing scientists have begun to build and apply comprehensive decision support models that link statistical models of purchase behavior to CLV metrics (e.g., Rust, Zeithaml, and Lemon 2000). In these models, the firm's ultimate goal is to "maximize"—not just measure—customer lifetime value. To do so, the firm must be able to forecast CLV, and consequently each CLV component, for an individual customer or segment under different scenarios.

Inputs and Outputs: Assumptions About Revenue and Cost Structures

To forecast CLV, firms must know the response of customers to marketing actions based on statistical models of purchase behavior and how marketing and operational costs are distributed across customers. The identification and measurement of CLV components in the current time period can be difficult, but it is even more challenging to determine what revenues and costs streams are relevant in the future. Calculating cash inflows from individual customers is likely to require separate models to determine growth in sales per customer (arising from repeat purchases and cross-buying) and changes in margins per customer (which depend on cost structures and are linked to operations). Marketing costs will typically include promotional costs aimed at retention (Berger and Nasr-Bechwati 2001) and investments in technology, service operations, employees, and quality improvement programs. Firms may wish to conduct their analyses under several different sets of assumptions. However, it is also important to identify future decisions that may dramatically alter revenue streams, such as promotional programs designed to stimulate repeat purchases (Berger and Nasr 1998).

Optimization Issues

Segments. Firms must not only optimize investment-level decisions, which consider the entire customer base as a single entity but also optimize the allocation of resources across individual customer segments to maximize profitability. For example, Heilman, Bowman, and Wright (2000) studied how brand preferences and responses to marketing activity evolve for consumers during their entire lifetime of purchasing in a category. They develop a theoretical framework that begins with a consumer's first-ever purchase in a category and describes subsequent purchases as components of sequential purchasing stages. To test their theory, they estimate a logit-mixture model with time-varying parameters using panel data on first-time parents from two categories of baby products. Although price elasticity declines (becomes less negative) during a customer's lifetime of purchasing in the diaper category, the extent of the decline varies across the three segments found in their data. Together with the results for intrinsic brand preferences, these suggest opportunities for varying marketing actions during a customers' lifetime of purchasing to enhance profitability. Simulation results are presented showing how profitability varies under competing pricing scenarios depending on which segment(s) is targeted and how price is varied during the target customers' lifetime of purchasing in the category (p. 148).

Channels. The interaction between different marketing mix instruments may lead to differential allocation of resources across marketing channels. Consequently, researchers and practitioners must work to develop a robust optimization framework for the allocation of marketing resources (given the response coefficients) across customer segments and within each segment across different channels of communication. This framework will typically be based on a profit function that incorporates the predicted purchase activity of a customer based on integrated marketing strategies, the resultant expected future revenue from the customer, and the variable costs of contact with each customer.

Time. A resource allocation strategy entails the distribution of expenditures over time and across marketing actions. For example, Venkatesan and Kumar (2001) estimated parameters of customer response functions from historical data and incorporated them into a net present value CLV function for each individual customer to obtain optimal levels of customer contact frequencies across different segments that maximize profitability. The customer contact levels across different channels of communication appear in both the revenue side and the cost side of the CLV equation. A genetic algorithm is used to derive the optimal levels of contact desired for each individual customer. There is utility to using genetic algorithms in this case given the need to maximize the response from customers, while simultaneously minimizing the cost involved in contacting the customers—a multiobjective optimization. One useful application of deriving optimal values of contact levels using the CLV function is that the results obtained can be directly applied to any economic value-added analyses of customers. Managers can use these optimal contact levels as a guideline to intervene when customers are predicted to become inactive, using a ramp technique where they start intervening, employing the lowest possible cost, and then increment the contact level until either the customer makes a purchase or the optimal contact level for the given customer is exceeded.

RESEARCH CHALLENGES IN CONSIDERING THE CUSTOMER AS A STRATEGIC ASSET

In this section, we identify four key research challenges in studying customer asset management. In our view, these challenges must be attacked from a variety of perspectives and with a variety of tools. There is a need for more theoretical work regarding customer behavior, analytic models to identify normative firm behavior, dynamic process studies of how customer responses to marketing actions vary over time, and meta-analyses to discover how contextual factors influence the relationship between marketing actions and CLV. In the following paragraphs, we use the four steps in our conceptual framework to frame our research challenges.

Database Creation: Rethinking Our Conceptualization of Loyalty

The creation of a database guided by marketing intelligence raises a key question: What is a "loyal" customer? The responses of a loyal customer are complex and multidimensional (Oliver 1999; Wind 1970; Zeithaml 2000). When an asset is purchased, the firm can usually determine the revenue streams associated with it. If the asset is sold to another entity, the firm is compensated, and the firm can purchase insurance against the possibility that the asset is lost or destroyed. However, when the firm considers an individual customer as an asset, the association between the customer and the revenue streams that accrue to the firm is much more tenuous and difficult to identify. A customer who makes a purchase from a firm may subsequently purchase again, purchase from a competitor, or engage in positive or negative word-of mouth behavior. Dowling and Uncles (1997) suggested that "polygamous loyalty" describes the complex behavior exhibited by customers. Because few customers allocate 100% of their purchases in a category to a single firm, it may be more useful to consider a customer's loyalty to be divided between brands. Thus, the firm's uncertainty about customer loyalty can be overcome by forecasting the likelihood that customers in a given market segment will engage in specific behaviors. Hence, "share of customer"—the expected percentage of business from a particular customer—can provide a measure of loyalty that is useful in CLV calculations (Rust, Zeithaml, and Lemon 2000). Thus, it is possible to calculate a dependable "expected value" estimate for the return on the customer asset.

What is the definition of "losing" a customer? The statistical issues associated with forecasts of customer behavior are complex. However, models have been developed to determine whether customers are still alive (i.e., active) and at what point they are likely to become inactive (Allenby, Leone, and Jen 1999; Bolton 1998; Schmittlein, Morrison, and Colombo 1987). However, when a customer becomes inactive, he or she is not necessarily lost forever. Even in industries with contractual arrangements between customers and firms, a customer may switch to another firm and then return to purchase from the original firm. For example, consumers switch their long-distance carriers periodically. Because a firm already has some level of familiarity with customers who are no longer active, it is possible that the reacquisition cost for a former customer would be less than the acquisition cost for a new customer. Thus, the estimation of matrices that describe how customers switch between competitors over time can be important (cf. Rust, Zeithaml, and Lemon 2000). Sometimes, for the purpose of modeling, a customer who has been inactive for a sufficient period of time can be considered a new customer when he or she is "reacquired."

Challenges in Segmenting Customers and Modeling Their Purchase Patterns

Statistical models of purchase behavior pose three key technical challenges to marketing scientists. First, customer touch and purchase histories are typically characterized by censoring and truncation, as well as sample selection bias, that necessitate sophisticated estimation procedures (cf. Heckman 1976, 1979; Lee, Maddala, and Trost 1980). Second, customers' responses depend on the marketing actions of competitors and the marketing actions of the firm. Information about competitors' marketing actions is typically unavailable to the firm when it creates its customer database, resulting in the omission of important predictor variables from customer response functions. This omission biases response function coefficients, and this bias is not easily corrected.

Third, comprehensive models of purchase behavior will require a system of simultaneous equations, where the dependent variables are various dimensions of customer purchase behavior and the predictor variables include a firm's conventional marketing and operations activities, as well as the type, medium, and frequency of touch. A system of simultaneous equations is important for two practical reasons. A marketing mix variable that increases one form of purchase behavior, such as cross-buying of new products or services, may have little or no effect on another form of purchase behavior, such as usage levels of existing products or services (e.g., Verhoef, Franses, and Hoekstra 2001). In addition, a marketing mix variable that influences purchase behavior may have feedback effects. For example, a firm may use CLV estimates to target certain market segments with loyalty programs, whereas the existence of loyalty programs alters customers' purchase behavior and consequently influences the calculation of CLV programs (Bolton, Kannan, and Bramlett 2000). This feature also creates simultaneity among marketing actions and customer purchase behaviors, which necessitates more sophisticated statistical estimation procedures.

Forecasting Challenges: Simultaneity and the Incorporation of Competition

There are significant challenges to developing comprehensive decision models that both capture the complexity of CLV financial calculations and incorporate statistical submodels for purchase behavior. Most important, firms forecasting the value of the customer base face the same challenge that we previously identified in our discussion of statistical models of purchase behavior, namely, incorporating simultaneity between decisions and outcomes. Specifically, it is possible that forecasts of CLV have a bearing on a firm's marketing strategies, whereas the firm's marketing strategies influence CLV forecasts. Consequently, it is more appropriate to view CLV as a dynamic measure that changes in response to a firm's marketing actions. As such, CLV should not be treated solely as an exogenous variable that is estimated (typically based on "static" assumptions) and used as input into marketing decisions. Accurate forecasts of the future value of the customer base require a rich conceptualization (and modeling) of the reciprocal relationship between marketing actions and CLV. As yet, the reciprocal relationship between marketing actions and CLV has not been addressed in the marketing literature, and it is a rich area for future research. Alternative approaches to understanding this relationship include applications of more elaborate decision support systems, judgmental forecasts, or analytic modeling.

A related issue that has also seldom been addressed in CLV forecasts is the inclusion of competitive activities into models of customers' purchase behavior and CLV forecasts. Clearly, firms must be able to calculate CLV under different environmental circumstances—and these circumstances include competitive activity by other firms in the industry. Otherwise, a firm's marketing actions will be confounded by the actions of competitors. For example, customers who are considered attractive due to high CLV forecasts and who are consequently targeted by a firm's marketing actions are likely to be equally attractive to competitors. Furthermore, customers who make their first purchase in response to a firm's promotional activities may be "deal prone" so that their subsequent purchases (from the firm or its competitors) are also sensitive to promotional activities.

Managers and researchers are still grappling with the difficulties of building CLV models when information about such activities is unavailable or sparse. Although it is ideal to include a variety of competitive effects in CLV models, the sheer number and unpredictability of potential competitive factors may overwhelm the modeling efforts and impede research progress in this domain.[2] As such, simplifying assumptions that hold certain difficult-to-track competitive factors constant or limit the time horizon of analysis to a duration within which the competitive scenario is likely to be reasonably stable may be necessary for modeling efforts to make contributions to both knowledge and practice. In addition, it may be more efficient to build short-term, limited-scope models and recalibrate them as competitive conditions change, rather than to pursue the challenging—and potentially elusive—goal of building more comprehensive models that attempt to capture all the dynamics and complexities of competition.

MANAGERIAL CHALLENGES IN CONSIDERING THE CUSTOMER AS A STRATEGIC ASSET

Create a Vision of Change Within the Firm

A few specialized customer asset management (CAM) models have been developed in the arena of direct marketing (Dwyer 1989; Keane and Wang 1995), but a comprehensive and context-rich model of customer asset management does not yet exist. Hence, at this stage, a firm may well ask, "Where do we go when there is no working model that has been shown to be effective in our industry?" Firms should begin by shifting to a customer-centered focus, enhancing relevant resources and capabilities, and developing suitable CAM metrics (as described elsewhere in this journal) and (finally) implementing new resource allocation strategies.

In "the Profitable Product Death Spiral," Rust, Zeithaml, and Lemon (2000) observed that the long-term consequence of a product-focused mind-set can be the erosion of the customer base to the point where its overall value is insufficient to support firm operations. Instead, firms should manage their customer base in the same way they manage their physical assets—by making profitable investments in value-producing areas. Although these issues are well recognized by many firms, the challenge for managers is finding a starting point. Many firms will find it useful to conduct a pilot study—using a random sample of customers or a purposive sample of a particular segment—to learn more about how these database issues affect them. Or, they may conduct studies that entail special data collection and integration efforts that are not routinely carried out. Alternatively, they may outsource certain database management functions. In some instances, when a database reaches a size such that the retrieval of information or the analysis of that information becomes inefficient, the firm must consider modifying its criteria for future inclusion and integration of the data or reducing the amount of information that is stored (Leeflang and Wittink 2000).

Another starting point for firms is a shift to focusing on key marketing metrics. Improvements in key marketing metrics—such as customer satisfaction (e.g., Fornell et al. 1996), brand equity (e.g., Keller 1998), and loyalty or share of customer (e.g., Reichheld 1996), can enhance the value of the customer base in the same way that an investment in technology enhances manufacturing capability. Such metrics are leading indicators of how the firm will perform in the future, whereas financial and accounting measures reflect how it has performed in the past and how it is currently performing. Firms rely on different marketing metrics depending on the degree of product differentiation and the complexity of customer decision processes in their markets (Rust, Zeithaml, and Lemon 2000). Analogously, firms' benchmarking and "best practice" efforts should focus their efforts on seeking out the firms with the best methods of managing their customer bases.

Developing Resources and Capabilities to Implement CAM Initiatives

As firms adopt a CAM focus, organizational processes and structure must be realigned to match their objectives.

2. We are indebted to an unknown reviewer for prompting these additional thoughts.

According to Teece, Pisano, and Shuen (1997), there are three aspects to such efforts: coordination, learning, and reconfiguration. First, the firm must organize itself around its customer segments and the separate drivers of CLV creation (cf. Blattberg, Getz, and Thomas 2001). For example, Rust, Zeithaml, and Lemon (2000) suggested organizing the firm's efforts around value, brand, and retention equity. Second, the customer-focused firm must also be able to learn from evaluating the outcomes of strategic and tactical decisions according to whether they increased or decreased the value of the customer base in the long term, rather than emphasizing short-term profitability. Third, as the external environment changes, there will constantly be a need to reconfigure organizational structures and processes to match evolving customer needs. For example, the market research function may need to expand to include the enhancement of traditional, transaction-based management information systems.

Earlier, we discussed the types of information that should be included in a CAM database. Beyond these considerations, the firm may need to develop new methods of data collection, change how it communicates with customers, and invest in new technology that supports customer-asset-friendly applications. A particular problem in the implementation of electronic commerce initiatives is that "back-end" operations function independently of "front-end" customer sales and service. Cross-functional integration is vital to the implementation of a CAM framework (Zellner 2000). For instance, the traditional marketing research function should coordinate with the information systems function to integrate survey-based data about customers' future purchase intentions with internal information in the firm's databases about customers' actual purchase histories. Likewise, both of these functions should also liaise with the accounting function to facilitate the determination and integration of individual customers' (or customer segments') revenue and cost streams. Equally important, CAM systems must be robust so that they produce stable and meaningful results that are not unduly sensitive to model misspecification, measurement error, uncertainty in forecasts, and so forth.

Firms must ensure that technology is deployed throughout the organization to leverage employee effort and enhance interactions with customers. Advances in technology have given rise to a new movement termed "customerization," in which firms offer custom-made products and services to every customer (Wind and Rangaswamy 2000). However, research has found that the greatest source of dissatisfaction for customers in technology-based (e.g., Web-based) service encounters is technology failure (Meuter et al. 2000). The increasing deployment of technology is changing services from "low-tech, high-touch" interactions—emphasizing interpersonal communications— to "high-tech, low-touch" interactions. This transition must be thoughtfully managed (Bitner, Brown, and Meuter 2000).

Allocation of Resources

Firms must learn about the value of their customers and integrate that learning in action (Woodruff 1997). The key challenge for managers is the coordination and integration of marketing actions over time (Parasuraman 1997). All four steps of our framework—database creation, market segmentation, forecasting customer purchase behavior, and resource allocation—have a temporal dimension. The firm must orchestrate specific marketing actions over time (e.g., selection of marketing communication vehicles, frequency of customer touches) to create unified strategies that are organized around the drivers of customer equity and thereby build customer value. The firm's customer value metric must also be a tool to integrate and evaluate the firm's strategies across functions (e.g., marketing, operations, human resources, technology) and borders (e.g., cultural, geographic). Finally, in addition to maximizing the value of its own customer base, the firm must consider cooperative strategies with network partners and other environmental management strategies (Zeithaml and Zeithaml 1984).

CONCLUDING REMARKS

In recent years, marketing practitioners and researchers have made important contributions to our understanding of how firms relate to their markets and how firms can manage their customers as assets. Considerable progress has been made in a very short time, and this article has attempted to outline some of the key features and challenges that have emerged. The purpose of this article has been to develop an overall framework that describes how marketing actions influence customer value and to discuss how customers can be viewed and treated as assets of the firm. In our view, this framework is a starting point for CAM. It highlights critical issues regarding CAM that academic researchers may wish to explore in future research and attempts to provide guidance to managers involved in CAM implementation efforts. However, much more work remains to be done.

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Paul D. Berger is a professor of marketing at Boston University, Boston.

Ruth N. Bolton is a professor in the Owen Graduate School of Management at Vanderbilt University, Nashville, Tennessee.

Douglas Bowman is an associate professor of marketing in the Goizueta Business School at Emory University, Atlanta, Georgia.

Elten Briggs is a doctoral candidate in the Michael F. Price College of Business at the University of Oklahoma, Norman.

V. Kumar is the ING chair professor and director of the ING Center for Financial Services at the University of Connecticut, Storrs.

A. Parasuraman is professor and holder of the James W. McLamore Chair in Marketing of the University of Miami, Coral Gables, Florida.

Creed Terry is executive vice president of marketing at Vector Marketing Corporation, Olean, New York.