V. Kumar & Werner Reinartz

Creating Enduring Customer Value

One of the most important tasks in marketing is to create and communicate value to customers to drive their satisfaction, loyalty, and profitability. In this study, the authors assume that customer value is a dual concept. First, in order to be successful, firms (and the marketing function) have to create perceived value for customers. Toward that end, marketers have to measure customer perceived value and have to provide customer perceptions of value through marketing-mix elements. Second, customers in return give value through multiple forms of engagement (customer lifetime value, in the widest sense) for the organization. Therefore, marketers need to measure and manage this value of the customer(s) to the firm and have to incorporate this aspect into real-time marketing decisions. The authors integrate and synthesize existing findings, show the best practices of implementation, and highlight future research avenues.

Keywords: customer value, perceived value, customer lifetime value, CLV models, customer engagement

A 1991 *BusinessWeek* article describes the notion of "perceived value" as "the new marketing mania" and "the way to sell in the '90s" (Power 1991). Morris Holbrook (1994, p. 22) wrote, "despite this obvious importance of customer value to the study of marketing in general and buyer behavior in particular, consumer researchers have thus far devoted surprisingly little attention to central questions concerning the nature of value." Moving forward to 2014, the Marketing Science Institute (MSI) specifies in its biannual Research Priorities (among its top priorities), "One of the most important tasks in marketing is to create and communicate value to customers to drive their satisfaction, loyalty, and profitability. Any insights in this area have significant implications for the long-term financial health of an organization. It truly is at the heart of what marketing is all about." Out of the 30 Dow Jones (United States) and 30 DAX (Germany) companies, 50% of the companies' vision or mission statements explicitly mention the notion of value creation for customers and/or stakeholders. For example, American Express's mission statement includes the sentence, "We provide outstanding products and unsurpassed service that, together, deliver premium value to our customers." Taken together, these high-level observations serve to underline the importance that the customer value aspect has had in the past and is continuing to have.

Clearly, business is about creating value. The purpose of a sustainable business is, first, to create value for customers[1] and, second, to extract some of that customer value in the form of profit, thereby creating value for the firm. Thus, the key underlying premise of this article is that customer value is a dual concept. First, in order to be successful, firms (and the marketing function) have to create perceived value for customers. In that sense, value is defined as overall assessment of the utility of an offering[2] according to perceptions of what is received and what is given (Zeithaml 1988). Second, customers provide value (customer lifetime value [CLV], in the widest sense) for the organization. For the firms/decision makers who allocate resources to markets, customers, and products, the challenge is to dynamically align resources spent on customers and products in order to simultaneously generate value both to and from customers.

We believe that aligning the customer-perceived value with customer-generated value vis-à-vis resource allocation is a research challenge that needs careful and comprehensive attention. In this article, we focus on this alignment by examining the specifics of this resource allocation challenge. More specifically, our goal is to answer the following concrete research questions:

1. What is value to the customer? What do we know?
2. How should (customer perceptions of) product and service value be measured? How can key drivers of customer value be identified and calibrated?
3. How should the value *from* the customer be measured and managed?
4. What are the drivers of customer value? How can they be incorporated in real-time marketing decisions?

V. Kumar (VK) is Regents Professor, Richard and Susan Lenny Distinguished Chair, Professor in Marketing, Executive Director of the Center for Excellence in Brand and Customer Management, and Director of the PhD Program in Marketing, J. Mack Robinson College of Business, Georgia State University; V. Kumar is also honored as the Chang Jiang Scholar, Huazhong University of Science and Technology, China; TIAS Fellow, Texas A&M University, College Station, TX; and ISB Senior Fellow, Indian School of Business. (e-mail: vk@gsu.edu). Werner Reinartz is Professor of Marketing and Director of the Center of Research in Retailing, University of Cologne (e-mail: werner.reinartz@uni-koeln.de). The authors thank the Marketing Science Institute and Kevin Keller for providing them the opportunity to contribute to this topic. They thank the guest editors of this special issue, as well as Sarang Sunder, Maren Becker, Manual Berkmann, Mark Elsner, Vanessa Junc, Monika Käuferle, Annette Ptok, Julian Wichmann, and three anonymous reviewers for their valuable suggestions on an earlier version of this manuscript. They thank Bharath Rajan for his valuable assistance in this study and Renu for copy editing an earlier version of this manuscript.

[1]We use the term "customer" to denote a consumer as well as a business customer.

[2]We use the notion of "offering" to indicate physical products, services, brands, or a combination thereof.

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What Is Value to Customers? What Do We Know?

Regardless of whether a physical good or a service is demanded by individuals for final consumption (direct demand) or as an input factor used in providing other goods and services (derived demand), the fundamental economic principle of utility maximization remains the same. Whereas the utility maximization theory is used to study products meant for final consumption, the profit maximization principle is used to study the inputs used in the production of other products. The traditional model assumes that the customer has perfect information about product characteristics and associated costs, as well as stable preferences, and thus is able to perfectly construct his/her final objective function—an assumption that has of course been relaxed in multiple ways (e.g., Hauser and Shugan 1983).

Given the central role of the notion of value to the customer in the marketing literature, it is not surprising that the subject has been dealt with repeatedly (Anderson 1998; Anderson, Jain and Chintagunta 1993; Monroe 1971; Wilson 1995; Zeithaml 1988). In various definitions of "value," there is a reasonable variety in the spirit of describing the trade-off between "give" elements and "get" elements (Anderson, Kumar and Narus 2007; Sawyer and Dickson 1984). For the purpose of this article, we define perceived value as customers' net valuation of the perceived benefits accrued from an offering that is based on the costs they are willing to give up for the needs they are seeking to satisfy.

Perceived customer value of an offering is the aggregation of benefits that the customer is seeking, expecting, or experiencing and the undesired consequences (Gutman 1982) that come with them. Benefits and undesired consequences are the results of buying and consuming the offering, and these may accrue directly or indirectly and be immediate or delayed. The central aspect of this conceptualization is that customers choose actions that, ceteris paribus, maximize the desired consequences and minimize concurrent undesired consequences. Benefits (and undesired consequences) are generated through offering attributes. Benefits differ from attributes in that people receive benefits, whereas offerings have attributes (Gutman 1982). Thus, attributes are features or properties of an offering. De facto, customers will never perceive all objective attributes (clearly) but will form a composite perception that recognizes the respective attribute salience.

Although much of the literature conceptualizes price as one of many potential attributes, it is of course necessary to subsume all cost components separately. Besides price, these typically include a vast array of different transaction costs, as well as learning cost and risk. Interestingly, much of the marketing literature typically accounts for price as the *only* cost component of an offering, thereby neglecting the many different immediate and delayed types of costs that customers might incur.

Perceived attributes then are aggregated by customers through a categorization process into more abstract benefits in order to reduce information overload and to facilitate further processing. The means-end chain model (Gutman 1982; Howard 1977) and the Gray benefit chain (Young and Feigin 1975) are probably the most widely used conceptualizations behind this effect chain from *concrete* offering attributes mapping onto *abstract* benefits generated. The "house of quality" concept (Hauser and Clausing 1988) is another very successful attempt, originating from the operations and quality control domain, to map objective attributes with customer perceived benefits. Interestingly, this mapping process has been considered virtually only for the offering's attributes, but an expansive consideration of monetary and nonmonetary cost aspects (price, transaction costs, risks, privacy) seems absent from the literature.

Once customers construct an aggregate assessment of an offering's perceived value, this value acquires meaning in two ways. First, as a necessary condition for customers to perceive an offering to be of positive value, perceived benefits have to outweigh undesired consequences. Second, once this is the case (and assuming the customer has the required willingness and means to transact), the assessment of value of a single offering among a set of different offers (e.g., from a consideration set) requires a comparison standard. This comparison standard may be concurrent competitive offerings, expectations, or past experience (similar to Golder, Mitra, and Moorman's [2012] nomenclature, a "value stock" perspective). Once the customer determines an offer to be of highest value, behavioral (choice, loyalty, CLV) and attitudinal (satisfaction, loyalty) outcomes ensue.

To summarize, we can observe that customer perceived value is a central mediating construct, separate from quality, perceived benefits, and satisfaction. Moreover, despite the relevance of this construct in practice, the literature has for the most part not been looking at the customer perceived value construct per se and has either omitted it from conceptual models (e.g., Golder, Mitra, and Moorman 2012) or has used proxies, such as customer satisfaction, instead. Finally, the aspects of perceived cost and undesired consequences in customer value models are arguably underspecified and understudied.

How Should (Customer Perceptions of) Product and Service Value Be Measured? How Can Key Drivers of Customer Value Be Identified and Calibrated?

Measuring customer perceived value is the natural starting point before one can even consider giving recommendations with respect to the value-oriented management.

Customer Value Measurement

The key tasks to be completed are (1) measure overall perceived value, (2) measure the associated underlying attributes and benefits, and (3) determine the relative weights that link attributes/benefits to overall perceived value. Customers are seeking offerings that yield the highest expected value or utility. Because utility cannot be measured or observed directly, market researchers, psychologists, and economists have devised ways to proxy these utilities. There is a long tradition of utility/preference measurement in marketing that commonly uses compositional and decompositional methods to model consumer preferences (see Table 1).

TABLE 1
Overview of Value Measurement Approaches with Exemplary Studies

Measurement Approach	Exemplary Applications/ Sources	Focus/Starting Point	Outcome	Role/Treatment of Attributes	Role/Treatment of Benefits	Role/Treatment of Undesired Consequences	Data Input	Other
Compositional								
Multiattribute method	Gale (1994)	Prespecified quality and price attributes	Overall value assessment	Prespecified	Typically not considered	Prespecified, typically price only	Attributes are generated through focus groups or managerial intuition; attribute ratings and importance weights are collected directly by customer survey	Explicit consideration of competition possible (comparison with competitive offering)
Consumer perceived value multiitem scale	Sweeney and Soutar (2001) (PREVAL scale)	Prespecified higher-level dimensions (emotional value, social value, functional value)	Overall value score as well as underlying dimensions	Individual prespecified items to measure higher-level value dimensions	Several prespecified items allude to benefits of the offering	Individual prespecified items to measure value for money/ price (broader cost concept)	Customer survey	Does not allow for heterogeneity
Relationship value index	Ulaga and Eggert (2006)	Prespecified higher-level benefit dimensions	Value as higher-order construct, including weights that determine the influence of benefit and cost dimensions		Individual prespecified items to measure benefit dimensions	Individual prespecified items to measure various cost dimensions	Customer survey	Explicit consideration of competition possible (comparison with second-best supplier)
Decompositional								
Conjoint analysis	Toubia, Hauser, and Simester (2004) (Polyhedral adaptive choice-based conjoint analysis)	Stated preferences for hypothetical product configurations (attributes and price)	Part-worth estimates for each attribute level	Prespecified by market researchers (price is treated as an attribute)	Typically not considered, but could technically be incorporated	Typically price only (technically, other cost dimensions could be integrated)	Customer survey (relevant attributes have to be identified qualitatively through prior studies)	Allows for customer heterogeneity segments
Aggregate perceived value	Sinha and DeSarbo (1998)	Overall perceived value	Offering location on perceived value dimensions	Implied without being specified a priori	Implied without being specified a priori	Implied without being specified a priori; consideration of various cost dimensions	Customer survey	Allows for customer heterogeneity/ segments

TABLE 1
Continued

Measurement Approach	Exemplary Applications/ Sources	Focus/Starting Point	Outcome	Role/Treatment of Attributes	Role/Treatment of Benefits	Role/Treatment of Undesired Consequences	Data Input	Other
Auction (WTP)[a]	Wang, Venkatesh, and Chatterjee (2007) (incentive-compatible elicitation of the range in a consumer's reservation prices; ICERANGE)	Consumers indicate maximum WTP and state at which price point they are indifferent (incentive-aligned)	Consumer's reservation price range	Prespecified by given product (no variation)		Price only	Auction/ experiment (web-based or personal interview)	Incentive-aligned
Pay what you want (WTP)[a]	Kim, Natter, and Spann (2009)	Consumers directly state their WTP (seller has to accept any amount)	Insight into individual level of value perception (satisfaction)	Prespecified by given product (no variation)		Price only	Consumer survey after transaction	

[a]These measures approximate value by measuring the consumer's willingness to pay (WTP). Strictly speaking, they only yield an overall value assessment and do not provide the possibility of disentangling the value attached to underlying characteristics (except in the case of a very elaborate study design).

Compositional methods begin with a set of explicitly chosen attributes/benefits and use them as the basis for determining overall value evaluations. In the compositional approach, expected utility is a function of the product attributes or benefits and corresponding costs multiplied by their respective importance weights. The key premise here is that relevant attributes and their respective relevant levels are known to the decision maker, and customers follow largely a rational decision-making approach. This approach has found reasonable entrance into the managerial domain (e.g., Gale 1994; Sweeney and Soutar 2001; Ulaga and Eggert 2006).

In contrast, decompositional techniques attempt to infer underlying utilities from observed choice, that is, revealed preferences. They start with measures of preference for offerings or attribute bundles and use them to infer the value attached to underlying characteristics. The goal is to approximate offering value from the customer's willingness to pay. A vast literature covers the use of this approach and, therefore, the interested reader should consult those sources (Rao 2014). The key approaches include survey approaches, auctions, conjoint analysis, and field experiments, with some of these methods having been widely used. Moreover, in the past 30 years, there has been a strong recognition that normative decision models are usually violated (Huber, Payne, and Puto 1982), and an entire stream of behavioral decision theory research has unfolded (Simonson 2015) that details the wide range of systematic deviations that can occur when customers attempt to assess value.

From the firm's perspective, the focus of the measurement approaches pertains mostly to tangible product attributes. The only intangible aspects that has seemingly found entry into these measurement models are the brand name dimension (e.g., Sinha and DeSarbo 1998) and aesthetic design aspects (Kumar 2015). Other intangible aspects seem absent. For example, in the context of digitization, what seems interesting is how an individual's perception of what constitutes value is influenced by others (i.e., network effects).

Treatment of Undesired Consequences (Costs)

The vast majority of attention in customer value measurement has been focused on the "get" side of the offering, namely, documenting the range and depth of attributes and benefits that are associated with the offering. The situation is starkly different with respect to the undesired consequences and cost aspects. Although perceived sacrifice is multidimensional, it is de facto operationalized as a unidimensional aspect in existing research (Teas and Agarwal 2000)—namely, on the price dimension. For example, in much of the conjoint analyses and logit models, price is introduced as another (linear) attribute variable (Hauser and Urban 1986, p. 448).

However, besides the mere cost (transaction price) of the offering to the customer, there is a large set of associated transaction costs, learning cost, and maintenance and life cycle cost, which are for the most part overlooked in existing models. In many situations, the monetary value of the sum of these nonprice costs easily outsizes the transaction price, typical in many business-to-business (B2B) settings (Anderson, Narus, and Narayandas 2009). Even more importantly, purchasing and consumption models that are based on usage (i.e., customer solutions) will become much more prevalent in the future (Ulaga and Eggert 2006; Ulaga and Reinartz 2011; Vargo and Lusch 2004). Therefore, the conceptualization and operationalization of a broader set of cost attributes is required in future customer value models.

Furthermore, in the context of digitization, a new cost-related aspect has been emerging. For many online services (e.g., Google Maps, Facebook), customers are not expected to pay in monetary terms. The core benefit is free of monetary charge from the end user's perspective. The monetization comes mainly from advertising revenues, with ads targeted at narrow segments or personal individual profiles. Here, we have a new situation wherein the monetary component within the undesired consequences has entirely vanished. Customers now have to understand the value of the personal information that they will give up in this exchange. Thus, customers pay in terms of less privacy instead of monetary outlays. In fact, some customers value privacy of personal information privacy so much that they would be willing to pay to preserve privacy—this then creates a market for privacy (Rust, Kannan, and Peng 2002). Moreover, Koukova, Kannan, and Kirmani (2012) hint at new option value that digitization may provide. They show how different formats of media (e.g., offline newspaper subscription vs. online formats) may provide complementary and incremental value to customers, depending on usage situation, as opposed to mere substitution. In other words, digitization will provide interesting and important new facets to the value debate. Table 2 presents a summary of related findings regarding the measurement of value and value drivers.

How Should Value from Customers Be Measured and Managed?

Until now we have reviewed (1) how firms can create value to the customer, (2) the ways to measure customer perceptions of value, and (3) the treatment of undesired consequences when managing customer value. However, creating and communicating perceived value to customers is better served when firms align perceived value with the resources they spend on customers, to ensure that the right amount of resources go toward managing perceived value. To identify the right amount of resources, it is important to ascertain the value that customers provide to the firm. Figure 1 illustrates the approach firms can adopt to derive value from customers.

As seen from Figure 1, the first step in deriving value is to realize the need for a forward-looking metric rather than a backward-looking one. Traditionally, firms have used metrics such as recency–frequency–monetary value (RFM), past customer value (PCV), share of wallet (SOW), and tenure/duration to measure the value of customers. The guidance from these metrics has driven decisions pertaining to the allocation of marketing resources. However, many of the traditional metrics focus on a backward-looking approach that only takes into consideration past activity of a customer, which leads to outdated information being used for customer selection and resource allocation. In contrast, the CLV metric is a forward-looking metric that takes into account the variable nature of customer behavior and enables firms to treat individual customers differentially and distinctly from each other depending

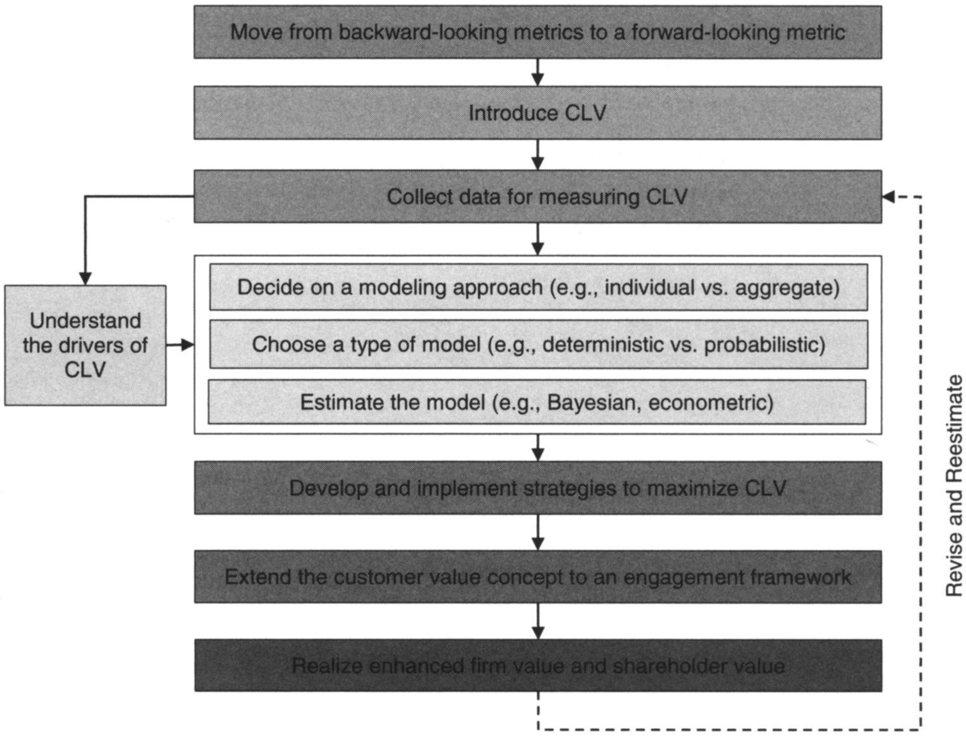
TABLE 2
Summary of Findings Pertaining to the Measurement of Value and Value Drivers

	Scholarly Contributions Thus Far	Tasks for Future Research
Perceived attributes and benefits	• Deriving underlying choice-relevant attributes using decompositional approaches • Understanding of longitudinal, situational, and cross-sectional heterogeneity.	• Understand whether and how attributes simultaneously pay into a given benefit • Broaden conceptualization and measurement of intangible attributes and benefits
Perceived costs and undesired consequences	• Inclusion of price as key (cost-related) variable	• Define conceptualization and operationalization of a broader set of cost-related attributes • Include new cost-related aspects due to digitization
Perceived value	• Deriving customer perceived value using compositional approaches • Measurement of customer perceived value through willingness to pay • Accommodating for incentive alignment and heterogeneity across time, customers, and product categories • Recognition of systematic violations of value maximization principle	• Examine value of personal information (context of digitization) • Examine influence of value perception by social network

on their contributions to the company. Amid the backward-versus-forward-looking distinction, it is also important to note the role of big data. Using big data that contains past information (e.g., sales, revenue, marketing spending), it is possible to accurately predict future behavior of customers and, thus, compute their value to the firm. The use of big data, however, does come with the challenges relating to the quality of data, data visualization, computing capabilities, and ability to obtain meaningful results. Nevertheless, the point to be noted here is the importance of being able to look into the future in determining the future value of customers, as opposed to relying on insights from past value contributions.

Realizing the need for a forward-looking metric is the most critical step for a firm. Once this has been achieved, the subsequent steps only strengthen the firm's position in cultivating a customer-centric organization. The following sections describe

FIGURE 1
Approach to Deriving Value from the Customer



the other steps identified in Figure 1 that put in place a cyclical process involving data collection, deciding on the modeling approach and the type of model, estimating the model, identifying the drivers of CLV, developing and implementing CLV-based strategies, extending CLV into a customer engagement framework, and reaping the benefits through higher firm value.

Firms have realized that just as customers derive value from the products/services being offered, firms, too, derive value from the customer base. Kumar and Reinartz (2012) define this value from the customer as "the economic value of the customer relationship to the firm—expressed on the basis of contribution margin or net profit" (p. 4). When firms identify the value provided by customers, they will be able to (1) better manage their costs, (2) post increases in revenues and profits, (3) realize better return on investment (ROI), (4) acquire and retain profitable customers, and (5) realign marketing resources to maximize customer value.

More so than customers' past and current contributions to the firm, a crucial factor is their contribution in future periods. It is this future component that is of immense interest to academicians and practitioners. The concept of future value contribution has been conceptualized in the form of CLV. The CLV metric has been conceptualized as the present value of future profits generated from a customer over his or her lifetime with the firm (Venkatesan and Kumar 2004). Estimating CLV helps the firm to treat each customer differently according to his or her contribution, rather than treating all customers in a similar fashion. Furthermore, the sum total of lifetime value of all customers of the firm represents the customer equity (CE) of the firm. In other words, CLV is a disaggregate measure of customer profitability, and CE is an aggregate measure. After computing the CLV of its customers, a firm can develop strategies such as optimally allocating its limited resources, identifying the next products that customers are likely to purchase, and balancing acquisition and retention efforts, among others, to achieve maximum return.

Modeling Approaches to CLV

In measuring CLV, marketing literature presents a rich variety of measurement approaches. However, the main objective across all approaches is clear—identify, maintain, and nurture profitable customers. The approaches can be categorized into two broad categories: the aggregate approach and the individual approach. In the aggregate approach, the average lifetime value of a customer is derived from the lifetime value of a cohort or segment, or even a firm. This level of measurement helps firms in evaluating the overall effectiveness of the marketing plan but not in customizing strategies for customers. In the individual approach, the CLV of one customer over his or her entire lifetime with the firm is computed. This level of measurement helps firms personalize strategies according to customer needs and the future profitability potential of the customer. Web Appendix A lists the aggregate and individual approaches to measuring CLV. Table 3 provides an overview of the select literature from the extensive field of CLV.

Types of CLV Models

Over the past two decades, research on CLV has covered a wide range of business conditions through the modeling approaches. This coverage has expanded the scope and application of CLV-based models for a multitude of industries and markets. This section discusses some of the popular modeling approaches from the extant literature.

Estimating models independently. Most models, barring few (Niraj, Gupta, and Narasimhan 2001; Venkatesan, Kumar, and Bohling 2007), focus on predicting future revenue and apply a constant gross margin and retention cost. Venkatesan and Kumar (2004) use a generalized gamma distribution to model interpurchase time and employ panel-data regression methodologies to model the contribution margin. They consider various supplier-specific factors (channel communication) and customer characteristics (involvement, switching costs, and previous behavior) as the antecedents of purchase frequency and contribution margin. Web Appendix B provides details on the independent models. Given the factors identified, purchase frequency and contribution margin are modeled separately, and the equation of CLV is specified as

$$\text{(1)} \qquad CLV_{it} = \sum_{t=1}^{T_i} \frac{GC_{it}}{(1+r)^{t/f_i}} - \sum_{l=1}^{n} \frac{\sum_m MC_{i,m,l}}{(1+r)^l},$$

where $GC_{i,t}$ is the gross contribution from customer i in purchase occasion t; $MC_{i,m,l}$ is the marketing cost for customer i in communication channel m in time period l; f_i, or frequency, is 12/expint$_i$ (where expint$_i$ is the expected interpurchase time for customer i); r is the discount rate; n is the number of years to forecast; and T_i is number of purchases made by customer i.

Estimating models simultaneously. Endogeneity is a statistical issue in the CLV model that relates directly to causation. When purchase frequency, marketing cost, and gross contribution are predicted independently, it becomes unclear whether it is current MC that leads to future GC or current GC that leads to future MC. In addition, the issue of heterogeneity relates to the customer profiles and has been found to influence purchase quantity and timing significantly (Allenby, Leone, and Jen 1999). When different customers respond differently to marketing messages, the contribution margin model must reflect this variation by allowing the regression weights to be different for each customer. Simultaneously modeling purchase frequency, MC, and GC solves both these issues and provides more accurate results.

Venkatesan, Kumar, and Bohling (2007) use Bayesian decision theory to address the uncertainty in customer response to marketing actions in a B2B setting. In this regard, they model the three parameters simultaneously. In the business-to-consumer (B2C) setting, studies have developed a joint model for purchase timing and quantity. For instance, Boatwright, Borle, and Kadane (2003) use the Conway–Maxwell–Poisson distribution to jointly model the purchase timing and purchase quantity for an online grocery retailer. Similarly, Chintagunta (1993) models the incidence of purchase at each time interval and the purchase quantity for grocery purchases by customers who make regular and frequent visits to a grocery store. By simultaneously modeling the parameters, it is possible to obtain an early-warning indication of abrupt changes in interpurchase times and purchase quantities for a customer. When individual customers/customer segments that exhibit

TABLE 3
Summary of Select CLV Literature

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Rust, Kumar, and Venkatesan (2011)	Use Monte Carlo simulation algorithm to predict customer purchase propensity, profit, and firm marketing actions.	Empirical	Monte Carlo simulation	High-technology services	The proposed model provides large improvements in prediction over the simpler models shown in literature.
Pfeifer (2011)	Use company-reported data to estimate the total CLV of a firm's current customers.	Empirical	Autoregressive (first-order)	Netflix	The study offers guidance about how to estimate retention rate and revenue per renewal when the reporting period spans multiple renewal periods.
Fader and Hardie (2010)	Develop a model of relationship duration that can be used to predict retention rates beyond the observed retention rates.	Empirical	Shifted beta geometric	Any industry	Failing to account for cohort-level retention-rate dynamics leads to biased estimates of the residual value of a customer.
Kumar (2010)	Study a multimedia multichannel communication framework based on CLV.	Conceptual	—	Retailing	Maximizing firm's profitability is critical for understanding drivers of CLV and CRV.
Kumar and Shah (2009)	Link customer equity (determined by the CLV metric) to market capitalization.	Empirical	Multinomial logit	High-technology services, retailing	Marketing strategies targeted at maximizing CLV can increase firm value and, thus, ultimately, stock price.
Kumar et al. (2008)	Show the implementation of CLV at IBM and its effects on profitability and resource allocation.	Empirical	Seemingly unrelated regression	High-technology services	CLV-based reallocation of marketing resources yielded a $20 million revenue increase without any additional resource investment.
Benoit and Van den Poel (2009)	Analyze CLV by means of quantile regression and compare the effects of the covariates.	Empirical	Quantile regression	Financial services	The study provides insights into the effects of the covariates on the conditional CLV distribution that may be missed by traditional least squares.
Donkers, Verhoef, and De Jong (2007)	Predict CLV in multiservice industry.	Empirical	Probit, parametric duration, nonparametric duration	Insurance services	Simple models perform well. Focusing on customer retention is not enough; cross-buying also needs to be accounted for.
Fader, Hardie, and Jerath (2007)	Demonstrate the use of Pareto/NBD models of repeat buying for computing CLV.	Empirical	Pareto/NBD	Case analysis	Different types of economic efficiencies for acquisition strategies and customer segmentation can be made through this model.
Fader, Hardie, and Lee (2005)	Propose a new model that links RFM metric with CLV using isovalue curves.	Empirical	Pareto/NBD	Online music website	Isovalue curves are highly nonlinear because customers with low recency values but high frequency present lower CLV than customers who have lower frequency.
Rust, Lemon, and Zeithaml (2004)	Present a framework that enables competing marketing strategy options to be traded off on the basis of projected financial returns.	Empirical	Logit	Airline	The framework enables a "what-if" evaluation of marketing ROI, given a particular shift in customer perceptions.

TABLE 3
Continued

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Venkatesan and Kumar (2004)	Develop a dynamic framework to maintain/improve customer relationships through optimal allocation of marketing resources and maximize CLV simultaneously.	Empirical	Generalized gamma distribution, genetic algorithms	High-technology services	Marketing contacts over various channels influence CLV nonlinearly. CLV-based customer selection provides higher profits in the future compared with other metrics.
Reinartz and Kumar (2003)	Develop a framework to compute CLV and identify factors that explain the variation in profitable lifetime duration.	Empirical	NBD/Pareto	Catalog retailer, high-technology services	The study demonstrates the superiority of CLV framework by comparing it with other traditional frameworks.
Libai, Narayandas, and Humby (2002)	Introduce a segment-based approach for customer probability analysis.	Conceptual	—	Retailer	The proposed approach retains the actionable information associated with individual-level analysis while also maintaining the simplicity of the more aggregate-level models.
Reinartz and Kumar (2000)	Propose a method of computing CLV to test the propositions between customer loyalty and profitability.	Empirical	NBD/Pareto	High-technology services	Although loyal consumers demand premium service and believe they deserve lower prices, they are not always profitable, nor do they contribute more to profits in the long run.
Pfeifer and Carraway (2000)	Introduce the use of Markov chain models for modeling customer relationships and CLV.	Empirical	Markov chain	Catalog company	Markov chain models can handle complicated customer relationship situations. They can also handle some complicated situations that algebraic solutions cannot.
Berger and Nasr (1998)	Present mathematical models for determination of CLV.	Conceptual	—	Illustrative examples	The study introduces the general classes of CLV models.

such a warning are identified, firms can implement appropriate customer relationship management (CRM) initiatives and customized marketing actions to each individual or to each customer segment.

Another setting in which simultaneous modeling has been offered is in winning back lost customers. Losing customers for good can be a significant setback for a firm's customer management efforts. While studies have demonstrated the merits of preventing customers from defecting (Bolton 1998, Bolton and Lemon 1999, Lemon, White, and Winer 2002), it is also important to look into ways of winning back lost customers. Kumar, Bhagwat, and Zhang (2015) study whether firms should chase a lost customer by investigating the impact of the reason for defection on reacquisition and second-lifetime duration and profitability. They achieve this by jointly estimating customer reacquisition, second-lifetime duration, and second-lifetime profitability per month. Web Appendix B provides details on these simultaneous models.

Brand-switching approach. Using information about the focal brand and the competing brands, Rust, Lemon, and Zeithaml (2004) model acquisition and retention of customers in the context of brand switching. This approach requires collecting information on the brand purchased in the previous purchase occasion, the probability of purchasing different brands, and individual-specific CE driver ratings from the customers. Through a Markov switching matrix, the individual customers' probability of switching from one brand to another based on individual-level utilities is modeled. The probability thus calculated is multiplied by the contribution per purchase to arrive at the customer's expected contribution to each brand for each future purchase. The summation of expected contribution over a fixed time period, after adjustments are made for the time value of money, produces the CLV for the customer. Web Appendix B provides more details on the CLV model specification.

Monte Carlo simulation algorithm. Another approach adopted by researchers to investigate the value created by customers is the simulation method. While managerial heuristics and empirical models have uncovered important insights on customer value, studies have also investigated the use of simulation models. The reason for exploring simulation methods stems from relatively unsuccessful attempts at predicting future customer profitability, with very simple models often performing just as well as more sophisticated ones. For instance, Campbell and Frei (2004) find that it is easier to predict future profitability for some customers than for others, even for customers within the same profit tier. Similarly, Malthouse and Blattberg (2005) find that their best models misclassify most customers who are predicted to have high profitability. Furthermore, Donkers, Verhoef, and De Jong (2007) show that the simplest model they test performs the best and provides better predictions than other models. These studies make the case for alternative approaches, such as a simulation method.

Rust, Kumar, and Venkatesan (2011) present a Monte Carlo simulation method that can accurately predict future customer profitability and performs better than existing methods. They accomplish this in an "always-a-share" setting wherein there is no dormancy in a customer–firm relationship and customers never completely terminate their relationship with a firm. Thus, in this approach, firms measure future profitability of a customer by predicting his/her purchase pattern over a prediction period, but they do not predict when a customer will terminate the relationship with the firm. In this model, the profitability of a customer is measured in terms of total profits and net present value of profit. The predictions regarding customer behavior include (1) the propensity for customer i to purchase in each future time period t and (2) the profit provided by customer i given purchase in future time period t. While the predictions of customer behavior capture the revenue aspect, the marketing actions by the firm (e.g., number of sales calls, direct mail sent to a customer) capture the cost aspects; these aspects need to be predicted for accurate CLV measurement. Toward this end, the study proposes a single model framework that predicts customer purchase incidence (Pur_{it}), customer gross profit (Π_{it}) conditional on purchase, and firm marketing contacts (X_{it}) and also models the potential correlations among these factors. Web Appendix B provides more details on the joint probability model.

Customer migration model. Dwyer (1997) presents a customer migration model for CLV analysis that is applicable for the "always-a-share" typology. Accordingly, customer behavior can be predicted on the basis of historical probabilities of purchase, depending on recency and the current recency state in which the customer is located. Further generalizations include segmentation variables such as the RFM metric and other demographic variables. In several situations, RFM is used as a segmentation tool by classifying segments as "low RFM" and "high RFM." Other segmentation approaches include SOW and customer life cycle. Web Appendix B provides the approach to expressing CE.

Deterministic model. Deterministic models precisely model outcomes as determined by parameter values, relationship states, and initial conditions. These models focus on inputs and outputs and leave little room for variations. Typically, these models are used to study firm actions such as customer acquisition, customer retention, customer profitability, cross-buying behavior, and product return behavior (Reinartz and Kumar 2000, 2002, 2003). The basic form of the deterministic approach used to model CLV is described by Jain and Singh (2002) (see Web Appendix B for the basic model). While this model does not account for acquisition costs, other models assume a constant gross contribution margin and marketing costs (Berger and Nasr 1998). Several variations of this basic model have been proposed (e.g., Dwyer 1997). Blattberg, Getz, and Thomas (2001) provide a comprehensive way to calculate customer equity by accounting for the number of prospects, acquisition spending, and consumer segments.

Probabilistic model. In a probabilistic model, the observed behavior is viewed as the realization of an underlying stochastic process governed by latent (unobserved) behavioral characteristics, which, in turn, vary across individuals. The focus of this type of model is on describing (and predicting) the observed behavior instead of trying to explain differences in observed behavior as a function of covariates (as is the case with any regression model). In other words, this type of model assumes that consumers' behavior varies across the population according to some probability distribution (Gupta et al. 2006). Web

Appendix B provides details on the basic probabilistic model. Literature provides many models to estimate the CLV of a customer using the internal data of a company. One such approach defines CLV as a function of the time interval between e-mail contacts sent to a customer (Drèze and Bonfrer 2009). Using the data from the entertainment industry, this model estimates the relationship between the time interval and CLV. The objective is to find the optimal time interval for permission-based e-mails to a customer base. Apart from internal data, survey data can also be used to estimate the CE of a firm (see Rust, Lemon, and Zeithaml 2004; Rust, Zeithaml, and Lemon 2001).

Structural model. The issue of multiple discreteness (wherein consumers may purchase more than one brand in one purchase occasion) in studies of CLV has received attention in the literature (e.g., Kim, Allenby, and Rossi 2002; Manchanda, Ansari, and Gupta 1999). However, the results have been suboptimal because conclusions regarding the quantity decision could not be made effectively. Sunder, Kumar, and Zhao (2016) adopt a direct utility approach to structurally model multiple discreteness while accounting for variety-seeking behavior in the demand model in assessing CLV of consumers in the consumer packaged goods (CPG) setting. Furthermore, the study is conducted on a longitudinal transaction database and allows the budget to vary deterministically with time. In addition, this is the first study to unify choice, timing, and quantity decisions in a single equation, thereby providing a direct approach for assessing CLV. Web Appendix B details this approach.

As a summary, Table 4 provides a comparison of the approaches discussed in the previous sections, according to their merits and shortcomings.

What Are the Drivers of Customer Value? How Can Customer Value Be Incorporated in Making Real-Time Marketing Decisions?

Until now, we have discussed various models proposed for understanding and measuring value from customers. The choice of model is ultimately decided by the availability of data (volume and variety), time, and technical resources, as well as the intended use of the CLV measure. Furthermore, information on competitive actions brings marketplace realities into the decision-making process through game-theoretic approaches. The final choice of model notwithstanding, the results have to lead to managerial decision making that is also conducive to real-time modifications. This involves understanding the drivers of customer value. In discussing the real-time applications, we adopt a relative approach wherein we focus more on time intervals (e.g., frequency of buying, pattern of buying cycles, the need to revise CLV scores periodically) rather than immediate actions. In this regard, we survey and present research that has examined this aspect of real-time applications and provide related insights for implementation. This, we believe, will present a new perspective on the real-time nature of decision making.

The drivers of CLV determine the nature of the relationship between the firm and the customer, and they help estimate the level of profitability and the CLV of each customer. They have been classified into two types: exchange characteristics and customer heterogeneity (Reinartz and Kumar 2003). Exchange characteristics encompass the set of variables that define and describe relationship activities in the broadest sense. Customer heterogeneity refers to the demographic and psychographic indicators that help a firm in segmenting customers and managing customer–firm relationships. As expected, the nature of a business (whether B2B or B2C) determines the exchange characteristics and customer heterogeneity factors. Figure 2 lists the classification of these drivers in B2B and B2C settings.

Similarly, Palmatier et al. (2006) provide a synthesis of the several empirical studies that have investigated the drivers that lead to stronger customer–firm relationships, as observed through WOM, customer loyalty, sales-related performance, customer likelihood to repurchase, and customer–firm cooperation. These studies clearly identify the drivers that have the greatest impact on customer–seller relationships. However, as more investigations on the nature of customer–firm relationships are uncovered, we can expect the list of drivers to change.

Strategies for Maximizing CLV

Once the computation of CLV is completed, firms proceed to maximize this metric in order to reap its full benefits. The CLV metric assists marketers to increase future profitability of not just current customers but also prospects. Furthermore, the CLV metric is not just about the dollar value of future customer profitability. It extends beyond that and aids in strategy development on one or more of the following: customer acquisition, customer retention, balancing customer acquisition and retention, customer churn, and customer win-back.[3] While the importance of these five tasks in ensuring profitability is duly noted, this does not mean that "maximizing" each individual metric is the correct recipe for success. Firms can look into maximizing CLV from an optimization perspective wherein the elasticities of each of these factors can be studied. Such an endeavor might be a promising avenue for future research. This section highlights the importance of understanding these five tasks in developing the CRM playbook of an organization.

Customer acquisition. The expansive literature on customer acquisition has probed several important questions, such as the following:

- How likely is it that prospects will respond to our acquisition promotion?
- How many new customers can we acquire in this campaign?
- How many orders will each of our newly acquired customers place?
- How do the marketing variables, such as shipping fee, WOM referral, and promotion depth, influence prospects' response behavior?

[3]For more details, see the "Wheel-of-Fortune" strategies in Kumar (2008).

TABLE 4
Comparison of Select CLV Models

CLV Model Type	Merits	Shortcomings	Typical Data Requirements	Exemplar Study Setting
Aggregate approach	• Aids in evaluating overall effectiveness of marketing actions	• Not able to customize marketing strategies	• Publicly available firm-level data that includes information on margin, discount rate, and retention rate	• Both brick-and-mortar firms and online firms across all industries that are publicly traded
Independent estimation	• Easy to use • Aids in customer-level and firm-level strategy development	• Requires end-user transaction data • Creates endogeneity and heterogeneity issues • Does not include competition	• Customer-level data on transactions and customer-firm interactions from firm's internal records	• High technology
Simultaneous estimation	• Accounts for endogeneity and heterogeneity • More accurate results than independent estimation	• Model development and estimation is more complex	• Customer-level data from firm's internal records that includes information on purchase quantity, product upgrades, cross-buying, marketing communication, product returns, and frequency of contacts	• Telecommunications • High technology • Grocery stores
Brand-switching approach	• Can be used when the firm has cross-sectional and longitudinal database • Accounts for all types of marketing expenditures • Can accommodate competition	• Sample selection can play an important role in the accuracy of the metric • Often relies heavily on survey-based data, thus leading to an increase in sampling cost and survey biases	• Survey data from a sample of customers that includes data on purchase frequency, contribution margin, and brands purchased recently	• Airlines • Rental cars • Electronic stores • Grocery stores
Monte Carlo simulation algorithm	• Better predictive power over simpler competing models • Better understanding of customer profitability and firm value	• Cannot be used in a lost-for-good setting • Heavy reliance on long purchase histories	• Individual-level data from firm's internal records that includes information on purchase propensity, marketing contacts, and gross profit	• High technology (can also be used for actual and simulated data)
Customer migration model	• Considers probabilistic nature of customer purchases	• Can be used only in limited business settings	• Data from firm's internal records that includes purchase propensities and recency of purchase	• Catalog mailing • Direct marketing

TABLE 4
Continued

CLV Model Type	Merits	Shortcomings	Typical Data Requirements	Exemplar Study Setting
Deterministic model	• Higher predictive accuracy • Aids in firm-level strategy development	• Requires huge amounts of individual customer data • Does not consider the relationship between model parameters • Descriptive, but not prescriptive, and therefore less helpful in managerial decision making • Does not account for competition	• Segment-level data on marketing costs, acquisition rate, retention rate, and contribution margin from firm's internal records	• Financial services • High technology • Insurance • Apparel • Catalog retailing
Probabilistic model	• Can be used when the firm does not have a longitudinal database • Identification of subdrivers aids in better resource allocation	• Assumes purchase volume and interpurchase time to be exogenous • Calls for frequent updating of the model • Heavy reliance on data and lesser reliance on managerial insight	• Individual-level data from firm's internal records, such as recency of purchases, frequency of purchases, and value of transactions	• Magazines/catalogs • Entertainment • Internet • High technology • Airlines
Structural model	• Model based on theoretical underpinnings of consumer behavior • Can account for various salient aspects of consumer behavior (e.g., multiple discreteness, budgeting) that cannot be addressed by other methods • Aids in accurate out-of-sample prediction and managerial policy simulations	• Model development and estimation is very complex • Relies heavily on across and within variation in customer purchases	• Scanner panel data on brands purchased in an instance, imputed price information, household-level market share of competing brands, and budgetary constraints	• Consumer packaged goods

FIGURE 2
Drivers of CLV in B2B and B2C Settings

	B2B Firm	B2C Firm
Exchange Characteristics	• Past customer spending level • Cross-buying behavior • Purchase frequency • Recency of purchase • Past purchase activity • Marketing contacts by the firm	• Past customer spending level • Cross-buying behavior • Focused buying behavior • Average interpurchase time • Participation in loyalty programs • Customer returns • Customer-initiated contacts • Frequency of marketing contacts • Type of marketing contacts • Multichannel shopping • Consumer deal usage intensity • Coupon usage intensity
Customer Heterogeneity	Includes variables such as industry, annual revenue, and location of the business	Includes variables such as age, gender, spatial income, and physical location of the customers

- How long will the newly acquired customers stay with our companies?
- How much profit or value will this acquisition campaign bring to our companies?

To understand customer acquisition, it is important to pay attention to the business setting: noncontractual or contractual. In a noncontractual setting, customers can and do split their spending across several firms. As a result, observing when a customer ceases to be a customer becomes difficult for the firm. However, situations wherein customers develop strong relationships with firms do exist (e.g., strong preference toward a particular brand of coffee). In a contractual setting, firms enjoy a relatively continuous future cash flow for a period of time, and they know when customers terminate the relationship. Even in such settings, it is possible for customers to defect without notifying the firm (e.g., failure to renew a magazine subscription). Studies have developed different models to study these two business settings regarding factors such as the expected duration or time of the relationship with customers, the likelihood of a customer continuing the relationship, and indicators of defection at the end of a service period, among others. Table 5 lists a representative set of studies that have considered these issues and accounted for many of the problems that might occur in the model-building process.

A fundamental research interest in understanding customer acquisition is in identifying the probability of a customer being acquired. Several studies have explored this question and have uncovered valuable insights (Lix et al. 1995; Reinartz, Thomas, and Kumar 2005). For instance, Von Wangenheim and Bayón (2007) find that customer satisfaction influenced the number of WOM referrals, which had an impact on customer acquisition, and that the reception of a WOM referral had an increased marginal effect on the likelihood of a prospect to purchase. This is achieved by studying (1) whether prospects' purchase likelihood is a function of WOM referrals, and (2) whether the characteristics of the WOM referral source influence the probability that received WOM induces a purchase behavior. In a B2B setting, studies have investigated the role of referrals in customer acquisition. For instance, Hada, Grewal, and Lilien (2010) recognize the types of referrals (customer–to–potential customer referrals, horizontal referrals, and supplier-initiated referrals) and have developed the concept of referral equity to capture the net effect of all referrals for a supplier firm in the market. These authors further propose a framework for managing supplier-initiated referrals that incorporates the supplier and the supplier's management of the communication between the referrer and the potential customer. Godes (2012) explores the conditions and subsequent impact of firms launching referral programs. The study demonstrates that launching such programs increases the willingness to pay of the early adopters in the high-technology B2B market. In addition, Kumar, George, and Leone (2013) develop and test an approach to compute business reference value (BRV), identify the behavioral drivers of BRV, and offer strategies to target and manage the most promising customers on the basis of their CLV and BRV scores.

In addition to customer acquisition, the number of newly acquired customers and their initial order quantity are also important. While Lewis (2006b) identifies that shipping fees influence the customer acquisition process and the initial order size, Villanueva, Yoo, and Hanssens (2008) show that market channels also influence the customer acquisition process and the value that newly acquired customers will bring to the company. The latter study develops two functions: (1) the value-generating function, which links newly acquired customers' contributions to the firm's equity growth, and (2) the acquisition response function, which expresses the interactions between marketing spending and the number of acquisition. Using a three-variable vector autoregression modeling technique for data from an online retailer, the study finds that marketing-induced customers add

TABLE 5
Summary of Select Customer Acquisition Studies

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Hada, Grewal, and Lilien (2014)	Propose a framework that incorporates the supplier and their management of communication between the referrer and the potential customer.	Empirical	Triadic communication	Business analytic solutions	Influence of the supplier-selected referral on potential customers depends on supplier uncertainty, and perceived bias significantly reduces potential customers' supplier evaluation.
Kumar, George, and Leone (2013)	Measure, understand, and manage BRV.	Empirical	Binary choice model	Telecommunications, financial services	The study defines the concept of BRV, determines the drivers of BRV, and illuminates the role of measures in driving BRV.
Godes (2012)	Understand when and why a business should announce a referral program.	Empirical	Game theory	High-technology B2B	Reference program can serve as a partial substitute for an exclusive-use contract.
Villanueva, Yoo, and Hanssens (2008)	Propose and test an empirical model that captures long-term effects of customer acquisition on CE growth.	Empirical	Vector autoregression model using three variables	Web hosting company	Marketing-induced customers add more short-term value, but WOM customers add nearly twice as much long-term value to the firm.
Von Wangenheim and Bayón (2007)	Examine the links between customer satisfaction, WOM, and customer acquisition.	Empirical	Logistic regression	Energy market	The satisfaction–WOM link is nonlinear and is moderated by several customer involvement dimensions.
Lewis (2006a)	Examine the relationship between acquisition discount depth and the value of customer assets.	Empirical	Survival analysis	Newspaper and online grocer	Acquisition discount depth is negatively related to repeat-buying rates and customer asset value.
Lewis (2006b)	Study how shipping fee schedules affect customer acquisition, customer retention, and order size.	Empirical	System of linear regression	Online grocer	Higher shipping fees are associated with reduced ordering rates, and penalties for larger orders lead to reduced order size.
Thomas, Reinartz, and Kumar (2004)	Determine whether maximizing customer acquisition and customer retention separately maximizes profits.	Empirical	Standard right-censored Tobit	B2B high-technology manufacturer, pharmaceuticals, and catalog retailer	Decreasing marketing spending for the B2B firm and catalog retailer, and increasing spending to customers of the pharmaceutical firm, would increase total customer profitability.
Hansotia and Wang (1997)	Determine which prospects should be contacted, and present models to estimate response and customer value at the individual level.	Empirical	Probit and Tobit models	Motor club membership	The authors recommend that firms adopt a long-term view by looking beyond response to the actual behavior of customers once they are acquired.
Lix et al. (1995)	Link purchase-intention information from survey data.	Empirical	Linear regression and log-linear	Retailer	The study provides a methodology to achieve efficiency in other direct mail efforts.

more short-term value, but WOM customers add nearly twice as much long-term value to the firm. The study also demonstrates the long-term impact of different resource allocations for acquisition marketing using dynamic simulations.

Of course, making marketing decisions using the response probability, initial order quantity, and duration is not enough. Companies should select prospects to acquire according to their lifetime contribution, which can be termed lifetime value, CLV, or CE. For instance, Reinartz, Thomas, and Kumar (2005) estimate customer profitability with a standard right-censored Tobit model using a set of exogenous variables and including the predicted duration and response probability. The authors find that decreasing marketing spending for a B2B firm and catalog retailer and increasing spending to customers for a pharmaceutical firm leads to increases in total customer profitability.

Customer retention. Aside from customer acquisition, firms devote large amounts of resources toward customer retention practices. To gain a better understanding of customer retention and to advise firms in a better manner, studies have typically focused on answering the following questions:

- Will the recently acquired customer repurchase or not?
- What will be the lifetime duration of the customer (i.e., when will the customer churn)?
- Given that the customer is going to repurchase, (1) How many items is that customer going to purchase? (2) How much is that customer likely to spend? (3) Will the customer purchase in multiple product categories?
- What will firms have to do in order to retain a customer worth retaining?
- What is the long-term impact of this customer's purchase behavior on firm value?

Various studies have been conducted and many models have been developed to answer these questions. Table 6 shows a representative set of studies that have considered these issues and accounted for many of the problems that might occur in the model building process.

When to engage in the activity of retaining a customer can be a highly misunderstood and undervalued component in customer retention. Monitoring a customer's purchasing and attitudinal behavior is vital in understanding when a firm should aggressively and actively pursue his or her retention. This is important for three reasons. First, firms can often lose sight of a customer's loyalty and lose their profitable customers, thereby creating undue financial stress. Second, monitoring customer behavior allows the firm to identify the attitudinal changes in a customer. This is important because understanding the attitudinal changes of a customer with regard to the firm's brand advises the firm on how and when to be aggressive in its retention strategies for that particular customer. Finally, a defecting customer can cause harm to the firm's brand through negative WOM if the customer's defection is due to unmet needs. If such unmet needs prevail over a large set of customers, and if this possibility is not addressed, the negative WOM may quickly snowball into a serious issue, thereby damaging both the brand and firm value.

Determining how much to spend on a customer is an important assessment involved in identifying who and when to retain. Innovations in statistical modeling now allow firms to measure a customer's future value and profitability to the firm, which makes it easier to make decisions on how much to spend as compared with the future value. This logical approach to customer retention calls for data pertaining to several aspects of customer transactions over a period of time. With respect to modeling techniques required to understand customer retention, simulated maximum likelihood estimation is the most commonly used procedure. However, more advanced estimation techniques, such as Markov chain Monte Carlo, Bayesian estimation, and generalized method of moments, have been used. Understanding customer retention also calls for accounting for customers' responsiveness to retention efforts because this determines the method of communicating the intention to retain and the costs related to it.

Researchers and managers alike are placing higher importance on the study of customer retention and its impact on company profits. In both B2B and B2C firms, model-based approaches are becoming increasingly available, and thus necessary, in both contractual and noncontractual relationships. In developing strategies for firms, research studies have drawn insights from (1) explaining customer retention or defection (Bolton and Lemon 1999; Borle, Singh, and Jain 2008); (2) predicting the continued use of the service relationship through the customer's expected future use and overall satisfaction with the service (Lemon, White, and Winer 2002; Lewis 2006a); (3) predicting renewal of contracts using dynamic modeling (Bolton, Kannan, and Bramlett 2000), (4) modeling the probability of a member lapsing at a specific time using survival analysis (Bhattacharya 1998); (5) modeling the duration of relationship using the negative binomial distribution (NBD)/Pareto model and the proportional hazard model (Fader, Hardie, and Lee 2005; Reinartz and Kumar 2000; Schmittlein, Morrison, and Colombo 1987); (6) use of loyalty and rewards programs for retention (Leenheer et al. 2007; Meyer-Waarden 2007); and (7) assessing the impact of a reward program and other elements of the marketing mix (Anderson and Simester 2004; Schweidel, Fader, and Bradlow 2008).

An important strategy for retaining customers is to nurture their cross-buying behavior. It has been shown that when customers purchase more products or services from the same firm, they extend the duration of their relationship with the firm (Reinartz and Kumar 2003) and increase purchase frequency (Reinartz, Thomas, and Bascoul 2008). Cross-buying results not only in an increase in revenue contribution for the firm but also in more engagement with the firm, higher profit contribution, and higher switching costs (Kumar, George, and Pancras 2008). Although cross-buying has the potential to increase profitability, some firms (e.g., financial services firms) have encountered unprofitable customers despite taking efforts to promote cross-buying (Brown 2003). Greater customer cross-buying does not always result in higher customer profitability. Shah et al. (2012) study this phenomenon of unprofitable cross-buying and find that (1) customer cross-buying is not necessarily profitable for all customers of the firm and can in fact adversely affect a firm's bottom line, (2) persistent adverse customer behavior drives unprofitable customer cross-buying over time, and (3) a company's marketing policies and practices

TABLE 6
Summary of Select Customer Retention Studies

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Borle, Singh, and Jain (2008)	Estimate purchase-level CLV by jointly modeling purchase timing, purchase amount, and risk of customer defection	Empirical	Discrete-hazard, log-normal	Membership-based direct marketing company	Longer interpurchase times are associated with larger purchase amounts and greater risk of leaving the firm.
Schweidel, Fader, and Bradlow (2008)	Model customer retention that accounts for duration dependence, promotional effects, subscriber heterogeneity, cross-cohort effects, and seasonality.	Empirical	Proportional hazard	Telecommunications service	Inclusion of promotional effects improves the forecast accuracy of retention behavior, whereas including cross-cohort effects does not significantly improve it.
Fader and Hardie (2007)	Provide an alternative approach to survivor analysis for estimating customer tenure.	Empirical	Shifted beta geometric	Contractual subscription-based business	Proposed model offers useful diagnostic insights and is very easy to implement using Microsoft Excel.
Leenheer et al. (2007)	Develop a model on the relation between loyalty programs and purchase behavior.	Empirical	Type II Tobit	Grocery retailing	Model accounts for endogeneity of loyalty programs. Predictive validity of the proposed model is much better than that of the naïve model.
Meyer-Waarden (2007)	Examine the impact of loyalty programs on customer lifetime duration.	Empirical	Proportional hazard	Supermarket	The higher the share of consumer expenditures in a store, the longer the lifetime duration will be.
Bolton, Lemon, and Bramlett (2006)	Model a firm's repatronage behavior for service contracts.	Empirical	Random intercepts	Enterprise-level systems	Models of customer retention should incorporate the extent, variability, and timing of a supplier's service delivery over time.
Verhoef and Donkers (2005)	Investigate the impact of channels firms frequently use on customer loyalty and cross-buying.	Empirical	Probit	Financial services provider	Direct-mail acquisition channel performs poorly on retention and cross-selling; radio and TV perform poorly for retention only; and website performs well for retention.
Anderson and Simester (2004)	Investigate how the depth of a current price promotion affects future purchasing of first-time and established customers.	Empirical	Poisson, linear regression	Mail-order durable goods	Deeper price discounts in the current period increased future purchases by first-time customers but reduced future purchases by established customers.
Verhoef (2003)	Investigate the differential effects of customer relationship perceptions and relationship marketing instruments on customer retention and share over time.	Empirical	Tobit, probit	Financial services provider	Affective commitment and loyalty programs that provide economic incentives positively affect both customer retention and share development.

TABLE 6
Continued

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Lemon, White, and Winer (2002)	Examine the influence of customer future-focused considerations, over and above the effects of satisfaction, on the customer's decision to discontinue a service relationship.	Empirical	Logit	Interactive television entertainment service	Consumers are significantly forward-looking when they make the decision to continue (or discontinue) a service relationship.
Bolton, Kannan, and Bramlett (2000)	Investigate the conditions in which a loyalty program will have a positive effect on customer evaluations, behavior, and repurchase intentions.	Empirical	Logit	Financial services	Loyalty program members overlook negative evaluations of the company vis-à-vis competition.
Reinartz and Kumar (2000)	Test whether long-life customers are always profitable.	Empirical	NBD/Pareto	Catalog retailer	Long-life customers know their value to the company and demand premium service; they believe they deserve lower prices, and they spread positive word of mouth only if they feel *and* act loyal.
Bolton and Lemon (1999)	Quantify the relationship between customer satisfaction and subsequent service usage.	Empirical	Type I Tobit	Interactive television entertainment service and cellular service	Customers' usage levels can be managed through pricing strategies, communications, and dynamic customer satisfaction management.
Bhattacharya (1998)	Understand how members' characteristics relate to lapsing behavior in paid membership contexts.	Empirical	Hazard	Art museum	Hazard of lapsing is lowered with longer duration, enrollment in special interest groups, gift frequency, and higher interrenewal times.
Bolton (1998)	Develop a model of the duration of provider–customer relationship and the role of customer satisfaction.	Empirical	Proportional hazard	Cellular service	Relationship between duration times and satisfaction is stronger for customers who have more experience with the service organization.

TABLE 7
Summary of Select Balancing Customer Acquisition and Retention Studies

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Reinartz, Thomas, and Kumar (2005)	Develop a modeling framework for balancing resources between customer acquisition efforts and customer retention efforts.	Empirical	Probit two-stage least squares	B2B high-technology manufacturer	Firms can manage their customer bases profitably through resource allocation decisions that involve trade-offs between acquisition and retention initiatives.
Thomas (2001)	Establish that the customer acquisition process affects the customer retention process.	Empirical	Tobit	Airplane pilot membership	The proposed methodology corrects for biases in the customer retention analysis that result from assuming that customer acquisition and retention are independent processes.
Berger and Bechwati (2001)	Create a framework for the optimal allocation of promotion budget for customer acquisition and retention.	Conceptual	Decision calculus	—	The study discusses decisions about expenditure allocation between acquisition and retention in different market conditions.
Blattberg and Deighton (1996)	Find the optimal balance between acquisition and retention that maximizes customer equity.	Conceptual	Decision calculus	—	The authors recommend that once managers have determined the balance between acquisition and retention, they plan for each task separately.

could facilitate (or deter) the persistence of adverse customer behavioral traits associated with unprofitable cross-buying. Using data from five firms, the study finds that the firm with the most liberal product-return policy had the maximum level of unprofitable cross-buying due to excessive product returns.

Even though several studies have highlighted the importance of customer retention as a single link in the chain of CRM, many firms have not yet understood the larger comprehensive view of the CRM process. For instance, some managers still view customer acquisition and retention as separate processes. Although most studies assess acquisition and retention separately, the literature provides an abundance of direction through which firms can link the two together in order to improve their CRM process.

Balancing acquisition and retention. Apart from identifying the balance in marketing effort between acquisition and retention in order to maximize profitability, studies have addressed questions such as the following:

- What are the drivers of customer acquisition?
- After being acquired, how long can the customer be expected to stay with the firm?
- How much investment is required in order to keep the firm–customer relationship alive?
- Given the resource constraints, how much should be spent on acquisition efforts versus retention efforts to maximize long-term profitability?

In investigating such topics, researchers have modeled acquisition and retention both independently and jointly. Table 7 lists a select set of studies that have considered balancing customer acquisition and retention.

In modeling independently, Lewis (2006b) investigates whether shipping fees differentially influence customer acquisition and retention. In a system of simultaneous equations, the study examines the effects of shipping fees and other marketing variables on the number of new customers acquired, the average order size for new customers, and the number of daily orders and the average order size for established customers. Furthermore, to account for the possible correlation between various equations and the possibility of endogenously determined explanatory variables, the author estimates the equations using three-stage least squares.

In another study, Lewis (2006a) investigates the influence of customer acquisition promotion depth on customer retention, including repeat purchasing and duration. In an online retailing setting, the study adopts a logistic regression to model whether the customer makes a subsequent purchase within the next three quarters, using acquisition discount as an explanatory variable. Using data from the newspaper industry, the study adopts accelerated failure time models to model the time as a subscriber, using acquisition discount and its quadratic form as an explanatory variable. The study also examines the effects of acquisition discount on customer asset value.

Berger and Bechwati (2001) optimize the allocation of promotion budget between acquisition spending and retention spending. When companies are considering one market segment and using one promotion method, such as direct mailing, managers decide the allocation of existing budget between acquisition and retention to maximize CE.

In modeling acquisition and retention jointly, Thomas (2001) proposes a method known as a Tobit model with selection to account for the impact of the customer acquisition process on the retention process. The proposed model successfully links customer acquisition to retention because the length of a customer's lifetime is observed conditional on the customer being acquired. The model also establishes that the error term in the acquisition equation is possibly correlated with that in the retention equation. Finally, Reinartz, Thomas, and Kumar (2005) model customer acquisition, retention, and profitability together as a system of equations, using a probit two-stage least squares model and estimate it as a system of equations.

In summary, customer acquisition modeling is actually a probability prediction, and customer retention modeling essentially concerns the duration of customer lifetime. Acquisition probability can be estimated by a probit or logit model; hazard models can also be used if the timing of incidence is concerned. Duration data are usually right-censored, so Tobit or hazard models are by nature suitable estimation techniques. Researchers link acquisition and retention modeling either by specifying the correlation of the error terms in probability and duration models or by specifying the joint distribution of acquisition and retention for estimation.

Customer churn. Determining who is likely to churn is an essential step. This is possible by monitoring customer purchase behavior, attitudinal response, and other metrics that help identify customers who feel underappreciated or underserved. Customers who are likely to churn demonstrate "symptoms" of their dissatisfaction, such as fewer purchases, lower response to marketing communications, longer time between purchases, and so on. It is important to note that while customer retention and customer churn are similar concepts, the need to study customer churn separately is rooted in the business setting. Whereas customer retention applies to both noncontractual and contractual business settings, customer churn is relevant only in a contractual setting. Therefore, understanding customer churn becomes crucial in certain customer–firm relationships. In this regard, the CLV-based churn models provide directions on several topics, including the following:

- When are the customers likely to defect?
- Can we predict the time of churn for each customer?
- When should we intervene and prevent the customers from churning?
- How much do we spend on churn prevention with respect to a particular customer?

Table 8 shows a representative set of studies that investigate the customer churn process.

Researchers have strong interest in the causes of customer churn and switching behaviors. They have developed various models that include (1) modeling churn with time-varying covariates (Jamal and Bucklin 2006; Van den Poel and Lariviere 2004), (2) analyzing the mediation effects of customer status and partial defection on customer churn (Buckinx and Van den Poel 2005), (3) modeling churn using two cost-sensitive classifiers (Glady, Baesens, and Croux 2009; Lemmens and Croux 2006), (4) determining the factors that induce service switching (Capraro, Broniarczyk, and Srivastava 2003), and (5) analyzing the impact of price reductions on switching behavior (Danaher 2002).

Customer win-back. It is no surprise that it is not possible for firms to retain all acquired customers. When customers churn, managers usually consider this indicative of the end of the customers' life cycle with the firm. However, it does not have to be: firms can still win the lost customers back and give them a second life. Unlike new customers, lost customers have certain knowledge about the products and services of the company and have their own judgment on the attributes and functions of the products and services. While it is easier to approach lost customers because they have familiarity with the firm, lost customers often switch firms because they are not satisfied with the product, which makes it difficult for the reacquiring firm to change customers' attitudes and persuade them to come back. Furthermore, firms also have to consider whether it is worth trying to bring customers back to the firm—not all customers are worth chasing after they leave the firm.

Once a customer is likely to churn, the firm response vis-à-vis letting a customer go or winning the customer back is critical. Researchers have studied this phenomenon from three aspects:

- Should the firm intervene in customer churn?
- If so, how should the firm approach customers to win them back?
- What elements would help firms in reacquiring lost customers?

The answers to these questions will drive the optimal customer win-back strategy. Table 9 lists select literature that has explored the topic of customer win-back.

Stauss and Friege (1999) provide a conceptual framework for regaining lost customers that consists of analysis, actions, and controlling. The study contends that to determine customer value in the context of regain management, the lifetime value of the terminated relationship is not an appropriate measurement. Furthermore, Griffin and Lowenstein (2002) highlight the importance of highly trained win-back teams and provide a general outline for winning back lost customers. This study proposes that not all churned customers are contenders to be won back. Instead, firms should calculate second-lifetime value (SLTV), segment customers on the basis of SLTV, and evaluate customers in each segment to determine why they defected. In addition, Thomas, Blattberg, and Fox (2004) investigate the best price strategy for reacquisition of lapsed customers, using a split hazard model (or censored duration model). Using data from the newspaper publishing industry, this study finds that lowering reacquisition prices to increase the likelihood of reacquisition is an optimal strategy. Finally, Kumar, Bhagwat, and Zhang (2015) investigate whether lost customers are worth the investment in reacquisition and whether they will remain profitable if reacquired. The study finds that (1) the lost customers' first-lifetime experiences and behaviors, (2) the

TABLE 8
Summary of Select Customer Churn Studies

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Glady, Baesens, and Croux (2009)	Present a framework using a profit-sensitive loss function for the selection of the best classification techniques with respect to the estimated profit.	Empirical	Logistic regression, neural network, decision tree, cost-sensitive classifier	Retail financial services	Cost-sensitive approaches achieve good results in terms of the defined profit measure and overall classification.
Jamal and Bucklin (2006)	Study the empirical link between customer churn and factors such as customer service experience, failure recovery, and payment equity.	Empirical	Weibull hazard	Satellite television	Prediction of customer churn is significantly improved when heterogeneity is added to the churn rates and to the response parameters.
Lemmens and Croux (2006)	Investigate whether bagging and stochastic gradient boosting can improve churn prediction accuracy.	Empirical	Bagging and boosting classification trees	Wireless telecommunications	Bagging and boosting techniques significantly improve the classification performance, and balanced calibration sample reduces the classification error rate.
Buckinx and Van den Poel (2005)	Identify which of the currently behaviorally loyal customers are likely to (partially) churn in the future.	Empirical	Logistic regression, automatic relevance determination, neural network, random forests	CPG retailer	RFM variables are the best predictors of partial customer defection; variables such as customer relationship duration, mode of payment, cross-buying behavior, usage of promotions, and brand purchase behavior are moderately useful in attrition models.
Van den Poel and Lariviere (2004)	Develop a comprehensive retention model including time-varying covariates related to customer behavior.	Empirical	Proportional hazard	Financial services	Demographic characteristics, environmental changes, and interactive and continuous customer relationships affect retention.
Capraro, Broniarczyk, and Srivastava (2003)	Study repurchase decisions that involve an information-based evaluation of alternatives.	Empirical	Hierarchical logistic regression	Health insurance	After satisfaction level is accounted for, objective and subjective knowledge about alternatives directly affects defection likelihood.
Danaher (2002)	Derive a revenue-maximizing strategy for subscription services.	Field experiment	Time-series regression	Cellular service	Access and usage prices have different relative effects on demand and retention.

TABLE 9
Summary of Select Customer Win-Back Studies

Representative Studies	Study Focus	Study Type	Model Type	Study Setting	Insights
Kumar, Bhagwat, and Zhang (2015)	Demonstrate how lost customers' first-lifetime experiences and behaviors, the reason for defection, and the nature of the win-back offer made to lost customers are related to reacquisition likelihood, their second-lifetime duration, and second-lifetime profitability per month.	Empirical	Probit, right-censored Tobit, regression	Telecommunications service	The stronger a customer's first-lifetime relationship with the firm, the more likely the customer is to accept the win-back offer.
Homburg, Hoyer, and Stock (2007)	Test the relationship between customers' first-lifetime satisfaction and their reacquisition.	Empirical	Logistic regression	Telecommunications service	Health of the first-lifetime relationship is positively related to reacquisition likelihood; customer perceptions of fairness regarding win-back offer are positively related to reacquisition.
Tokman et al. (2007)	Identify the factors driving win-back offer effectiveness.	Quasi-experimental design	Analysis of variance	Auto repair and maintenance service	Price and service benefits provided in the win-back offer, social capital, and service importance are important in shaping customer switch-back intentions, regardless of previous satisfaction, regret, or delight with the new service provider.
Thomas, Blattberg, and Fox (2004)	Study the probability of customer reacquisition and the duration of the second lifetime, with a focus on the impact of the depth of the price discount.	Empirical	Split-hazard, Bayesian Markov chain Monte Carlo	Newspaper industry	For the win-back offer to be effective, it should consist of low promotional prices; successful reacquisition should be followed by price increases.
Stauss and Friege (1999)	Conceptual basis for "regain management" aimed at winning back customers who either give notice to terminate the business relationship or whose relationship has already ended.	Conceptual	—	—	Retention policy in service companies needs to be complemented by regain management.

reason for defection, and (3) the nature of the win-back offer made to lost customers are all related to the likelihood of the customers' reacquisition, their second-lifetime duration, and their second-lifetime profitability per month.

Customer win-back is a critical component within the overall CRM strategy, but it has received relatively less research attention than customer acquisition, retention, and churn. Firms must first be able to understand the drivers of customer reacquisition, customer duration in a second lifetime, and second-lifetime customer profitability before they can make accurate strategic decisions regarding which customers to try to win back, and what offers to provide to maximize customer profitability.

Extending CLV to Engage with Customers

Typically, customer contribution to firm profitability occurs (1) directly, through their purchases, and (2) indirectly, through their nonpurchase reactions, which include referring potential customers, influencing current and potential customers in their social network, and offering review/feedback for improvements. In this regard, Kumar et al. (2010) propose the customer engagement value framework, which can be used to identify and evaluate the right customer, who is successfully engaged with the firm and who generates value and positively contributes to the profits of the firm. The following discussion elaborates on customers' indirect contribution to value.

Role of referrals. Studies in this area have found that customers acquired through referrals are not only less expensive to acquire but also more valuable for the firm, as compared with customers acquired through traditional methods (Schmitt, Skiera, and Van den Bulte 2011; Villanueva, Yoo, and Hanssens 2008). For instance, Schmitt, Skiera, and Van den Bulte (2011) examine the difference in value derived from each customer depending on acquisition method, using customer data from a financial services firm. The study finds that referred customers are more profitable than nonreferred customers. However, Villanueva, Yoo, and Hanssens (2008) find that customers acquired through traditional techniques are more valuable in the short term to some extent, but referred customers are twice as valuable in the long term. In addition, the value differential becomes even larger when the disparity in acquisition costs is considered, due to the considerably lower costs of referrals. Table 10 summarizes the other key contributions of past research in this area.

Kumar, George, and Leone (2007) introduce the customer referral value (CRV) metric, which captures the net present value of the future profits of new customers who purchased the firm offerings as a result of the referral behavior of the current customer. Simply put, it represents the value of how firm-initiated and firm-incentivized customer referral programs can improve the profitability of the customer base by acquiring cost-effective prospects (Kumar, George, and Leone 2010). Most notably, this metric makes a distinction between the customers that initiated a relationship with the firm solely because of the referral and those that would have become customers even in the absence of a referral. Therefore, CRV includes both the acquisition savings and the profits of the future transactions of customers who join as a result of the referral. However, it includes only the acquisition savings of customers who would join anyway, because their future transactions would happen even in absence of the referral, so they cannot be attributed to the referrer.

Research in this area has focused on (1) developing models that use only a customer's actual past referral behavior to compute an individual customer's referral value (Kumar, George, and Leone 2007), (2) the identification of the behavioral drivers of CRV and the methods of soliciting referrals according to each customer's CLV and CRV scores (Kumar, George, and Leone 2010), and (3) studying referral behavior in a business setting, that is, BRV (Kumar, George, and Leone 2013). The BRV is defined as the ability of and degree to which a client's reference influences prospects to purchase. The BRV of each referencing client and the CLV of each referencing client and newly acquired client from the prospect pool are measured using a three-step method comprising (1) determining whether client references influenced the prospect's decision to adopt, (2) determining the influence each client reference had on the prospect's decision to adopt, and (3) computing the CLV of the converted prospect. Furthermore, Kumar, George, and Leone (2013) empirically determine the key drivers of BRV and recommend that a firm using a client-referencing strategy needs to leverage a portfolio of client references that includes clients with varied characteristics in order to match the client to the prospect successfully.

Valuing customer influences. The spread of information by WOM is a critical component in converting prospects into customers. To better understand the impact of WOM, several studies have called for its inclusion in customer value models (Hogan, Lemon, and Libai 2003; Libai et al. 2010). Research has investigated WOM propagation in the context of online referrals (Trusov, Bucklin, and Pauwels 2009) and the evolution of the network as a whole with every consecutive instance of WOM (Robins et al. 2007). Kumar et al. (2013) develop a framework to capture the value of an individual's WOM in terms of both its viral impact and the net sales that it facilitates through two key metrics—customer influence effect (CIE) and customer influence value (CIV). Whereas the CIE measures the net spread and influence of a message from a particular individual; the CIV calculates the monetary gain or loss realized by a firm that is attributable to a customer, through that customer's spread of positive or negative influence. The study implements the framework by creating and deploying a social media strategy at an ice cream retailer. By tracking these two metrics for the retailer, this study is able to demonstrate a 49% increase in brand awareness, 83% increase in ROI, and 40% increase in sales revenue growth rate. While most firms are still struggling with social media accountability, this study effectively shows the importance of CIE and CIV. Although these early studies illustrate the importance of valuing customer influences, more research is required to get a deeper understanding of this phenomenon.

Valuing customer knowledge contributions. Customers can add value to the company by helping elucidate customer preferences and participating in the knowledge development process. In this regard, beta site customers that use/review products and provide valuable feedback to firms are a great example of customer knowledge contribution. Studies have investigated the amount of value added by customers through their knowledge contributions. For instance, Füller, Matzler, and Hoppe (2008) find that brand community members who have a strong interest in the product and in the brand usually

TABLE 10
Summary of Select Customer Referral Behavior Studies

Representative Studies	Study Focus	Study Type	Model Type	B2B vs. B2C	Study Setting	Insights
Kumar, George, and Leone (2013)	Understand the role and value of client references in a business context.	Empirical	Logit	B2B	Telecommunications service, financial services	Firms can effectively use business references to pull in new customers. Rich media and similar companies are the key drivers of success.
Schmitt, Skiera, and Van den Bulte (2011)	Determine the extent of profitability and loyalty of referred customers.	Empirical	Regression, proportional hazard	B2C	Banking services	Referred customers (1) have a higher contribution margin initially, (2) have a sustained higher retention rate, and (3) are more valuable in the short and long run.
Kumar, George, and Leone (2010)	Determine the optimal customer targeting for referral marketing campaigns.	Empirical, field study	Bayesian Tobit	B2C	Financial services, retailing	Firms can effectively select customers within segments of high and low CLV/CRV for referral marketing campaigns using the drivers of CRV (dynamic targeting).
Villanueva, Yoo, and Hanssens (2008)	Establish a value-generating process by modeling the interactions between new customer acquisition and the growth of firm value.	Empirical	Vector autoregression	B2B	Web-hosting company	Marketing-induced customers add more short-term value, but WOM customers add nearly twice as much long-term value to the firm.
Kumar, George, and Leone (2007)	Compare customer segmentation according to CLV and CRV.	Conceptual	—	B2C	Telecommunications service, financial services	Customers with high CLV are not the same as customers with high CRV.
Ryu and Feick (2007)	Determine the effectiveness of rewards for referral marketing.	Field study	Analysis of covariance	B2C	MP3 players	Offering a reward does increase referral likelihood, but the size of the reward is not significant.
Hogan, Lemon, and Libai (2004)	Quantify the advertising ripple effect.	Conceptual	—	—	Hairstyling services	The WOM generated after an advertising-motivated purchase can be significant.
Hogan, Lemon, and Libai (2003)	Devise a method to account for social effects in the management of customers.	Empirical	Nonlinear least squares regression	B2C	Internet banking	The value of a lost customer changes as a function of the time in the product life cycle.

have extensive product knowledge and engage in product-related discussions and support each other in solving problems and generating new product ideas. With respect to the roles played by customers in this process, studies have categorized them into two categories: information providers and codevelopers (Fang 2008). In capturing the value contribution through knowledge sharing, Kumar et al. (2010) introduce the customer knowledge value (CKV) metric as the value a customer adds to the firm through his or her feedback. The need for computing the knowledge value contributed by customers has been recognized by studies that have posited that (1) tracking a customer's product or service expertise (which is correlated with the customer's CLV) can be valuable in assessing CKV (Von Hippel 1986), and (2) defected customers might contribute to CKV by sharing their reasons for leaving, allowing the firm to identify service improvement opportunities and increase its capability to detect at-risk customers (Stauss and Friege 1999; Tokman, Davis, and Lemon 2007). These studies constitute a nascent stream of research that has much promise.

Realizing Enhanced Firm and Shareholder Value

Customer equity represents the sum of the lifetime values of all customers of the firm. This topic has been a subject of constant attention; it has been shown to maximize the return on marketing investments and guide the allocation of the marketing budget (Blattberg, Getz, and Thomas 2001; Reinartz, Thomas, and Kumar 2005; Rust, Lemon, and Zeithaml 2004). For instance, Gupta, Hanssens, and Stuart (2004) show across multiple firms that customer value can be a method of firm valuation that is as good as a better than traditional accounting. They also quantify the impact of firm value resulting from improvements in retention, margin, and acquisition costs. Customer satisfaction has also been linked to higher firm value in that it increases immediate cash flows and creates future growth options (Fornell et al. 2006; Gruca and Rego 2005; Malshe and Agarwal 2015).

Kumar and Shah (2009) propose a framework to link the outcome of marketing initiatives (as measured by CE) to the firm's market capitalization (MC) (as determined by the stock price of the firm). The intuition behind this framework is that the stock price of the firm is based on the expected future cash flows of the firm. If cash flow is primarily generated from customers, an increase in CE (or cash flow from customers) should relate to an increase in MC (or the stock price of the firm). Such an approach would answer three important questions: (1) Can marketing strategies that increase CE also increase the stock price of the firm? (2) If so, can such increases in stock price be predicted on the basis of changes in CE? (3) Can the increases in the stock prices of the two firms be attributed to shareholder value creation?

To answer these questions, Kumar and Shah (2009) implement CLV-based strategies that are designed to strengthen the CRM practices of a firm. The implementation was done over a nine-month period in a B2B firm and a B2C firm, both *Fortune* 1,000 companies. At the end of the implementation, the study finds that the increases in stock price for the B2B firm and the B2C firm were approximately 32.8% and 57.6%, respectively. Furthermore, when the average monthly values of the stock price are plotted over time and compared with the actual average values of the stock prices of the two firms, the results indicate that it is possible to track the actual movement of stock prices within a maximum deviation range of 12%–13%. It is also found that the stock price of the B2B firm outperformed the S&P 500 by 200%, and the B2C firm outperformed the S&P 500 by 360%. Finally, the study also finds that the B2B firm's stock increases by 32.8% during the observation period, while its three closest competitors' stocks go up by an average of 12.1% over the same period. Similarly, the B2C firm's stock increases by 57.6%, while its three closest competitors' stocks go up by an average of 15.3% over the same period. These findings clearly demonstrate the linkage between CE and MC.

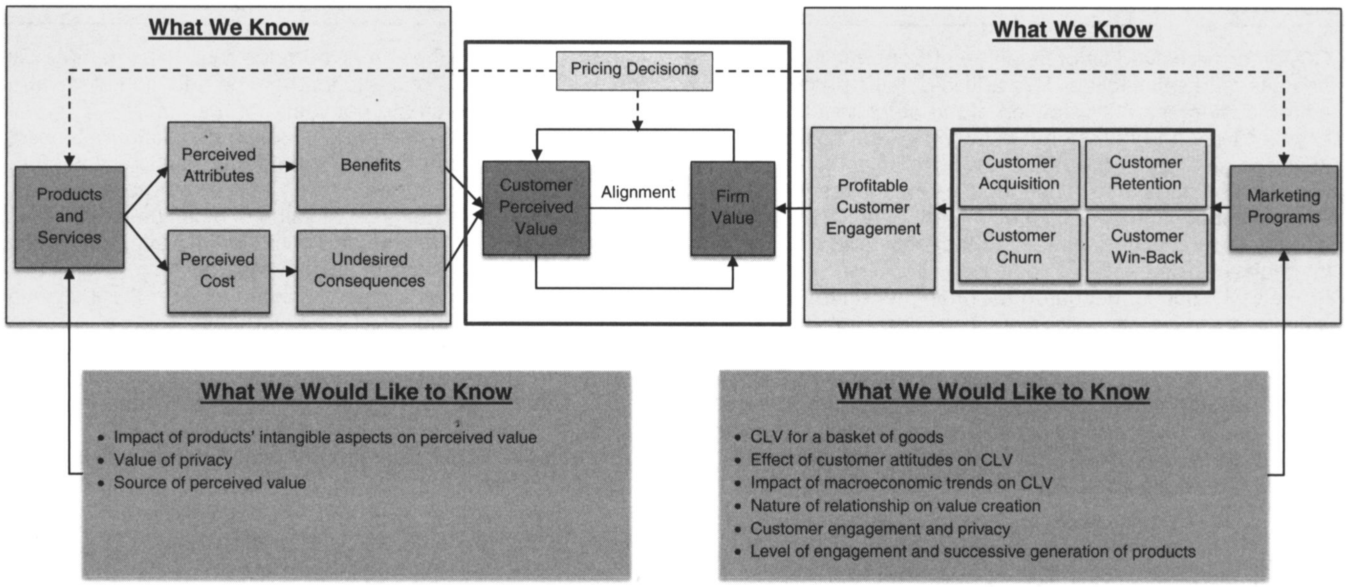
The studies discussed here sufficiently demonstrate the power of real-time decision making that firms would gain when the drivers of customer value and timely marketing interventions are carefully understood and coordinated. This implementation would not only refine marketing actions but also enhance value to the firm.

Key Insights and Future Research Directions

Extant marketing literature has investigated the concept of customers providing value to firms and have sought to understand the process of deriving value from customers, ways of measuring it, and strategies for maximizing it. The current study has discussed the knowledge created by researchers thus far in understanding customer value. This research has shown that value is created to and from the customers. While this creation happens fairly regularly, this process is beneficial only if it is long-lasting, which is possible only when the customer perceived value (i.e., value to customers) and firm value (i.e., value from customers) are aligned. This alignment, however, only happens over time. Furthermore, the alignment process is constantly shaped by what we know about value and the knowledge we still seek. When these two value sources are aligned, it leads to the creation of enduring customer value, as opposed to just value. The alignment is materialized through the appropriate setting of prices in a manner that reflects customer and competitive factors. In effect, there is a constant reevaluation from the firm's side vis-à-vis prices to ensure the value alignment to and from the customers. The setting of prices is subsequently reflected in the development of products and services, as well as in the designing of marketing campaigns. Figure 3 presents an organizing framework that describes the process of value alignment.

This study has uncovered some valuable insights that will be helpful in understanding the creation and communication of value. With regards to value to customers, this study has defined customer perceived value that incorporates both the "give versus get" perspective and the value-communicated aspect. Such an approach to defining and understanding perceived value highlights the importance of thinking beyond

FIGURE 3
Ensuring Value Alignment: An Organizing Framework



the value component, to include the costs given up for the benefits that are being sought. Following this definition, this study has identified three tasks for measuring customer perceptions of value: measuring overall perceived value, measuring the associated underlying attributes and benefits, and determining the relative weights of the attributes/benefits linked to overall perceived value. With respect to value from the customers, this study has identified that a forward-looking metric such as CLV is ideal in metricizing customer value contributions. Furthermore, this study has observed that to create net value for the firm, the perceived value that customers receive must be aligned with the resources spent on the customers, through the adoption of forward-looking metrics. To this end, CLV is identified as the metric (among the popularly used metrics) that most accurately computes the net present value of a customer according to his or her future transactions with the firm, after accounting for revenue, expense, and customer behavior. Various CLV-based strategies have been proposed that firms can use to maximize value from customers after computing CLV. Table 11 lists the key insights from this study.

Looking ahead, we would like to offer three key areas that could spur future research. First, we believe the Internet will attain even more dynamism in terms of the uses, abilities, and opportunities it presents. In this regard, the Internet of Things (IoT) is bound to offer several avenues for researchers and practitioners to identify and maximize ways to create value for firms and customers. With its origins in the supply chain context (Ashton 2009), the IoT now encompasses uses in virtually all areas, including health care, urban planning and management, emergency services, construction, environment monitoring, lifestyle, and sports management. The ready applicability to a wide range of industries is largely due to the connectivity to media and transportation channels the IoT provides to firms.

For instance, consider the case of a professional sports team. Sports fans would like to get to the sporting venues in time for the game and the other attractions offered. However, a game day brings with it the problems of traffic and changing weather conditions, which create challenges in finding the fastest route to the venue. With a key goal of ensuring fan satisfaction, a sports team could consider providing a wearable device to fans that would inform them of traffic conditions, road closures, and weather updates, in addition to team-related and game-related information. Such a device from the team management, apart from being a piece of fan merchandise, would also keep fans engaged with the team. The technology to create such a device is available through IoT, but how can firms create value from such an offering? To begin with, what value-based metric can be used to identify the fans who would receive such a device? Can such a device capture fan satisfaction effectively? How would the team view fan satisfaction at the venue and fan satisfaction getting to and coming from the venue? In other words, would an unpleasant experience away from the venue adversely influence a fan's satisfaction at the game and subsequently lead to a decline in loyalty? Furthermore, what insights could the team gain regarding fan experience on game day and the ways to mitigate any loss in following? How could the team capture these fan sentiments and use the device to offer a valuable proposition that both engages the fan with the team and ensures value to the team through consistent ticket sales?

Second, health and fitness consciousness has been on the rise, with fitness studios offering varied programs to suit every customer need. These paid options provide several customization options for users to design their visit and structure their fitness regimen. These options include scheduling visit times (some studios are even open 24 hours a day), personal training, designing meal plans, and studio

TABLE 11
Key Insights from This Study

Value to Customers	Value from Customers
• Customer perceived value is different from quality, perceived benefits, and satisfaction. This article defines perceived value as the customer's net valuation of the perceived benefits accrued from an offering that is based on the costs they are willing to give up for the needs they are seeking to satisfy. • Benefits and undesired consequences are the results of buying and consuming the offering (i.e., the attributes of the offering), and these may accrue directly or indirectly and may be immediate or delayed. • Perceived value is measured according to attributes, which may be objective attributes (i.e., produced attributes) or perceived attributes (i.e., experienced attributes). • Approaches to modeling consumer preferences have adopted two types of methods: compositional and decompositional. While the former is a set of explicitly chosen attributes/benefits that are used as the basis for determining overall value evaluations, the latter attempts to infer underlying utilities from observed choice. • Firms can create perceived value for customers through (1) leveraging their own capabilities, (2) aligning with customers' perception of what is valuable for them, and (3) claiming a differential advantage (e.g., premium or margin) over competitive offerings. • Customers form a judgment of value as a function of perceived, not actual, benefits and costs. • Measuring customer perceptions of value involves three key tasks: (1) measuring overall perceived value, (2) measuring the associated underlying attributes and benefits, and (3) determining the relative weights of the attributes/benefits linked to overall perceived value.	• Firms need to align the perceived value customers receive with the resources spent on them through the adoption of forward-looking metrics, to create net value for the firm. • Unlike backward-looking metrics, forward-looking metrics focus on the customer, rather than the product, and can be used to understand current clients as well as prospects. • CLV calculates the net present value of a customer according to his or her future transactions with the firm, after accounting for revenue, expense, and customer behavior. • CLV can be modeled at the aggregate level or the individual customer level. • CLV-based strategies can be used not only to maximize revenue, minimize costs, or both, but also help with customer acquisition and retention, balancing acquisition and retention, customer churn, and customer win-back. • The customer contribution to firm profitability occurs directly, through customer purchases, and also indirectly, through actions that might include referrals or influencing others via social networks, customer reviews, and feedback to the firm. • The concept of customer engagement value helps in the identification and evaluation of the right customer, who is successfully engaged with the firm, who generates value, and who positively contributes to the profits of the firm.

amenities, among others. In addition, fitness studios now have a strong online presence through blogs and social networking sites. They now interact with customers and fitness enthusiasts by exchanging fitness-related information. Consumers also have access to unpaid options such as fitness videos and predesigned fitness routines available on the Internet. While this option lacks customization, being available for free compensates for this dearth. Perhaps the major attraction of the unpaid option is the availability even during travel. However, some fitness studios also now have dedicated members' websites that offer health tips, along with tools to manage workout schedules through videos and instruction manuals, in addition to regular studio admission. From the perspective of a fitness studio, the challenge of such a site is twofold. First, how does the firm present its value proposition vis-à-vis other competing studios (e.g., www.my360gym.com)? Second, how does it fight the competition from the unpaid fitness options? In such cases, what other novel and innovative programs can be offered by fitness studios to attract customers? Furthermore, how can studios design, price, and offer online fitness material (text, audio, and video) that can effectively compete with the existing unpaid options? In addition, can studios exist only in the online format (e.g., www.booyafitness.com) without any physical presence, and if so, how would the value then be determined for a fitness customer?

Finally, household purchase decisions have received substantial research attention (e.g., Epp and Price 2008; Gupta, Hagerty, and Myers 1983). The decision-making roles typically include influencers, gatekeepers, deciders, buyers, users, and disposers. In situations in which the head of the household is the decider and buys a good, the product is intended either for personal use or common use. Household consumption is also known to be affected by scale economies, wherein the utilization rate of a good can be raised by increases in family size (Lazear and Michael 1980). In such conditions, for the purposes of identifying value and designing customer strategies, firms would benefit if they had answers to questions such as the following: (1) Is the good being purchased for personal use or common use? (2) Who will be paying for the good—the individual or the family? (3) Will a trade-off be necessary to buy the good, either by the individual or the family? (4) In the case of a common good, will the good hold the same value to all members of the household, and if not, how can the disparity be alleviated? (5) In the case of a common good, will there be any design changes necessary to satisfy all the users? (6) How should the media mix be designed such that the influencers of the household are reached with the right message, in the right format, and at the right time? (7) Given these questions regarding the decision-making roles, the usage of the good, and the awareness of the good, should firms compute the value as a comprehensive amount

TABLE 12
Future Research Directions

Value to the Customers	Value from the Customers
• The effect of customer costs and consumer needs on perceived value has been studied largely from the viewpoint of a product's tangible features. Intangible aspects, such as, for instance, the network effect on perceived value, have not been explored. Network effects have been addressed in the "value from customers" perspective (e.g., Kumar et al. 2013; Robins et al. 2007) to strengthen profitable customer–firm relationships. Future research could explore individuals' perception of value and its constituents in a network setting that exhibits influences across customers. • Studies of undesired consequences have explored the realm of privacy concerns primarily in an online business setting. However, a more comprehensive treatment of the value of privacy is required to better our understanding in terms of (1) quantifying the overall value of privacy, (2) determining the value of personal information that customers will be willing to give up for products with lower prices, and (3) establishing the offline product categories that privacy costs apply to customers. • In identifying the source of perceived value, while usage, costs, and profits involved have been considered, the nature of product has not been considered. Future studies could focus on the source of perceived value—simple product design or sophisticated product design.	• While Sunder, Kumar, and Zhao (2016) have bridged the gap in literature by proposing a structural approach to measuring CLV that incorporates the choice, timing, and quantity decisions of consumers to assess CLV in the CPG setting, future studies in this area can look into expanding the analysis for a basket of goods, and including stochastic shocks to the system that might influence the consumption. • Literature has shown that customer behavior influences CLV (Reinartz and Kumar 2003) and that customer attitudes influence customer behavior (e.g., Anderson 1998; Hogan, Lemon, and Libai 2003), which in turn influences CLV. But do customer attitudes directly influence CLV? Answering this question is bound to provide insights into the reasoning behind customer behavior and how they affect customer profitability. • While most CLV implementation studies account for marketing and financial variables, the macroeconomic trends remain unaccounted for. What approaches can we adopt to account for macroeconomic factors such as GDP growth rate, rate of unemployment, and so on, in the CLV implementation to make it more accurate and reflective of market realities? • Although the benefits of implementing customer engagement have been demonstrated, we need to know the nature of the relationship between level of engagement and value creation (e.g., linear or inverted U shaped). • Furthermore, what is the role of customer engagement in customer privacy issues? That is, if customers are engaged more, will they be less sensitive to sharing private information? • In realizing value through customer engagement, is it possible to identify which form of engagement will work with a certain type of customer? That is, can a customer provide value in all forms of engagement? • Research has identified other forms of engagement, such as gifting behavior. Bhagwat and Kumar (2015) propose that encouraging customers to take part in gifting behavior is one way to effectively engage them with the firm and to consequently see profitable outcomes. In this regard, are there any other forms of engagement that can lead to profits for the firm? • When firms launch products, the performance of the previous generation of products and the overall firm performance are challenged. For instance, whenever Apple launches a product (e.g., iPhones), the prices of the previous-generation products are lowered, prompting many consumers to wait for such a price drop to buy the earlier version. In this regard, does the level of engagement facilitate the adoption of successive generation of products, and if so, how? • CLV maximization can also be viewed from an optimization standpoint. Firms often plan and change their resource inputs. When the elasticities of factors such as customer acquisition, retention, and win-back are considered, the resulting optimization may lead to better-informed resource planning. • Despite the prevalence of coalition loyalty programs, they have received little attention in academic research. Future studies could investigate the profitability drivers of such loyalty programs. • The identification of the lifetime value for dealers (e.g., dealer lifetime value) would help firms such as car dealerships to find a reliable method of (re)allocating scarce marketing resources to the "best"-performing dealerships.

that accounts value derived by all the users of the household, or as a summation of individual values of all the users?

This study has also presented specific research areas regarding *value to* and *value from* the customers. With respect to value to the customers, for instance, this study recommends looking into the network effects because the effect of customer costs and consumer needs on perceived value has been studied largely from the viewpoint of a product's tangible features, while the intangible aspects, such as the network effects, have been explored by only a few studies (Kumar et al. 2013; Robins et al. 2007). Therefore, a more detailed investigation into this is required to broaden our understanding on delivering customer value.

Another issue that requires research attention is the case of privacy. In order to use online services, customers are required to share their personal information instead of being charged a fee. In effect, while customers get to use the services for free, the cost incurred is sharing personal information. Amid this growing digitization climate, firms now will have to understand (1) the value of shared private data, (2) the business settings in which such an option will (and will not) work, and (3) how the value proposition can be communicated to customers. Future research along these lines will be helpful in understanding the drivers of value in a digitized format and in customizing offerings to maximize value to and from customers.

With respect to value from customers, this study has identified several areas for future research. For instance, while a structural approach to measuring CLV that incorporates the choice, timing, and quantity decisions of consumers to assess CLV in the CPG setting has been proposed (Sunder, Kumar, and Zhao 2016), more studies in this area are needed to formalize this learning. Specifically, studies that can expand the specific product-level categorization to include a basket of goods will facilitate the study of CLV from a retailer's perspective. Such studies will likely result in (1) further refinements to the drivers of customer and retailer profitability, (2) better customization of product offerings, and (3) targeted store-level product promotions.

Another area that could be fruitful for research on CLV involves accounting for macroeconomic trends and new product introductions by competitors. Specifically, future studies should look into identifying approaches that can be adopted to account for macroeconomic factors such as GDP growth rate, rate of unemployment, inter- and intracountry variations, consumption and investment spending, and international trade balance in the CLV implementation to make it more accurate and reflective of market realities. In this regard, Kumar and Pansari (2016) have shown that national cultural dimensions affect the drivers of purchase frequency and contribution margin and that economic factors influence the components of CLV directly. In effect, the relative effects of the drivers of CLV are influenced by the differences in the macroeconomic trends of the countries as well as in the cultures of the countries. However, more studies across countries with different levels of economic stability/performance are needed to more thoroughly understand this result. These insights will be of use to firms that have international operations to plan their resource allocation well ahead of time.

Future studies could also focus on identifying the nature of the relationship between level of customer engagement and value creation (e.g., linear or inverted U shaped). This will help in refining the engagement strategies aimed at enhancing customer value creation. Furthermore, identifying newer forms of engagement would expand the number of avenues through which a firm could establish engagement. For instance, research has determined that encouraging customers to take part in gifting behavior effectively engages them with the firm and consequently leads to higher profits (Bhagwat and Kumar 2016). Future studies could investigate other forms of engagement that, when encouraged among customers, can lead to profits for the firm.

An area of loyalty that is gaining significant traction is coalition loyalty. Such a program brings together two or more companies to offer loyalty incentives across a wide spectrum of retail and service offerings (e.g., Star Alliance in the airline industry). These programs provide significant advantages such as shared operational costs, higher cross-selling potential, and a symbiotic relationship among participating companies (Lee, Lee, and Sohn 2013). Limited research in this area has found that service failure by one partner has a spillover effect on other partners (Schumann, Wünderlich, and Evanschitzky 2014), and positive spillover effects from one partner are reflected in cross-buying of other partners (Lemon and Von Wangenheim 2009). Future research could look into the profitability drivers of these programs to gain a better understanding of the outcomes.

Another area of research opportunity lies in determining the optimal balance of resource allocation between traditional and new media, and the role of each in maximizing ROI. The challenge here for researchers lies in determining the optimal mix of media options and how they should be prioritized among the customer deciles in order to maximize ROI. When the rebalancing of resources is linked back to customer acquisition, retention, and win-back initiatives, the results would lead to better informed resource planning.

The identification of lifetime value of distributors/dealers (e.g., car dealerships) is another area with opportunities for future research. In the case of U.S. car dealerships, auto manufacturers sell their cars through exclusive dealerships and/or dealerships that carry multiple brands. Here, the auto manufacturers need to find a reliable method of (re)allocating scarce marketing resources to the "best-"performing dealerships. In this regard, creating a "dealer lifetime value," classifying dealers as "high-value" or "low-value" and placing them in appropriate deciles, would help manufacturers solve the reallocation problem. Table 12 provides a compilation of topics that might be considered for future research.

This study has discussed the major developments in the CLV area of research and highlighted potential future research directions. Specific refinements and improvements can be expected in (1) approaching measurement of CLV, (2) understanding the drivers of CLV, and (c) gathering more empirical evidence regarding the various business application of CLV. When these developments feed into real-time decision making for marketers, marketing's accountability to the corporate boardroom will have been enhanced.

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