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Customer Lifetime Value — The Path to Profitability

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Abstract

This survey talks about Customer Lifetime Value (CLV) as a metric that would help managers make informed business decisions. While there have been prior articles that take an extensive and in-depth look at Customer Equity (CE)(Villanueva and Hanssens, 2007), this survey reviews the CLV metric in particular. The definition and approaches to compute CLV and the concept of customer equity are discussed in detail. Specifically, this survey provides methods for measuring CLV, the strategies for developing customer-centric strategies, the implementation of CLV strategies in a B2B and B2C setting, and the challenges faced by an organization in implementing a CLV-based framework. This survey details the importance of CLV as a metric in a marketer's toolkit and how it is relevant to managing customers.

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Introduction

Hewlett-Packard (HP) was going through a phase where the business was not too good. The company planned to initiate a customer relationship program to increase revenues. In the process, they had to confront organizational inconsistencies and inadequate customer information before starting the customer relationship program. Meanwhile, HP's multiple product teams were independently sending emails to their IT and non-IT customers armed with little knowledge of their customers' communication or product needs. Each team offered its customers only product promotions, as against a comprehensive HP solution.

HP wanted to launch a consolidated email marketing program that would enable them to gather and analyze useful data about new and current customers. Using this information, they planned to offer personalized and relevant communications on a consistent schedule. Initial research showed that customers wanted support information rather than marketing information. IT customers indicated the types of content they wished to receive, whereas non-IT customers expected HP to "figure out" what they wanted. After analyzing the problems, HP decided to provide customized marketing communications to improve customer satisfaction from IT and non-IT professionals. The solution was in establishing a one-to-one email personalization “engine” that periodically sends personalized email messages based on the customer’s product ownership, IT professionals, and content preferences. The personalized engine micro-segmented HP’s customers (rather than just segmenting the audience into large clusters) and sent out 50,000 to 100,000 different content combinations each month. The engine drew information from HP’s customer and content profiles, and placed the content in templates to create a customized monthly newsletter. Customers received information that is only relevant to them, with no overlap or duplication from other HP product teams.

Each content item in the message included a link to a web page, which enabled them to track the customer’s activity. Over time, their click-through behavior was recorded, and added to the information they provided when the customers subscribed to the newsletter. The newsletter was designed to provide usage tips at the right time to assist with business problems, to help the customer understand HP’s offerings, and to encourage the customer to continue ordering from HP. About half of the newsletter’s content relates to where the customer is in the product life-cycle at that time.

The results that were realized led to increased revenues, decreased costs and thereby increased profitability of customers. Apart from realizing annual sales of over $300 million, HP saved nearly $3.6 million annually in total marketing cost savings. A test comparing direct mail to the online incoming newsletter showed that an email costs only $7 per lead, while direct mail costs $163. Similarly, HP avoided costs by driving customers to direct inquiries to HP via email rather than by phone. Since HP spent only 3 to 8 cents per inquiry via email, rather than $15 for a phone call, almost $4.2 million was saved annually.[1]

The above example is a direct demonstration of the how effective management of customer relationships can be used to maximize profitability. HP, by concentrating on revenue maximization and cost minimization, has increased its profitability, and thereby has paved way for a market-based growth while carefully evaluating profitability and return on investment (ROI) of marketing activities. In other words, the

[1] http://www.acxiomdigital.com/clients/hp.asp

key to success lies in optimal allocation of resources across profitable customers and cost effective customer-specific communication.

This is very relevant in today's dynamic business environment, where the changing face of customers is a challenge to reckon with. Companies are increasingly faced with the arduous task of keeping track of their customers, maintaining consistency within the organization and satisfying customers' needs so as to enjoy continued patronage. It is imperative to build and maintain successful individual-level customer relationships in order to maximize profitability and ensure customer loyalty for future profitability. This is not an easy task to accomplish. Relationships with customers are not always secure. It is difficult to predict for how long a customer is going to stay with a firm in a non-contractual setting. Firms have to adopt innovative customer relationship management (CRM) strategies to manage customers and ensure higher profitability. Customer management strategies are aimed at addressing the needs of every customer and by developing a one-to-one relationship with them. CRM-based strategies can be adapted and implemented in a wide range of companies and sectors, and both in B2B and B2C settings. Companies, across various sectors, that have implemented this approach have increased their profitability significantly. However, all firms need not have individual-level relationships. For instance, in cases like a mass-merchandiser or a CPG company it may not be necessary to build one-to-one relationships.

It is important to note that the basic philosophy of customer-centric approach is to serve customers and thereby try to provide customized services to customers. Product-Centric firm is more focused at the portfolio of product and thereby concentrate on increasing the product line for customers, whereas Customer-Centric firms concentrate on portfolio of customers. Several new firms have challenged the product centric approach and have gained huge profits by adopting customer-centric approach. The product-centric and customer-centric approaches are explained in greater depth in Section 8 of this survey (Kumar, 2008). Therefore, in a customer-centric approach, assessing the value of a firm's customers becomes important. But, what is the value of a customer? Can customers be evaluated based only on their past contribution to the firm? Which metric is better in identifying the future worth of the customer? These are some of the questions a firm has to deal with before assessing the value of its customers. While answering these questions, it is important to note that customers' value has to be based on their contribution to the firm across the duration of their relationship with the firm. In simple terms, the value of a customer is the value the customer brings to the firm over his/her lifetime from the current period. Recent studies have shown that past contributions from a customer may not always reflect his or her future worth to the firm (Reinartz and Kumar, 2003). Therefore, there is a need for a metric that can objectively measure future profitability of the customer to the firm (Berger and Nasr, 1998).

This survey talks about Customer Lifetime Value (CLV) as a metric that would help managers answer these questions and make informed business decisions. While there have been prior articles that take an extensive and in-depth look at Customer Equity (CE) (Villanueva and Hanssens, 2007), this survey reviews the CLV metric in particular. The definition and approaches to compute CLV and the concept of CE are discussed in detail, later on in this survey. Specifically, this survey provides the methods of measuring CLV, the strategies for developing customer-centric strategies, the implementation of CLV strategies in a B2B and B2C setting, and the challenges faced by an organization in implementing a CLV-based framework. The following section details the importance of CLV as a metric in a marketer's toolkit and how it is relevant to managing customers.

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Why is Customer Lifetime Value Relevant and Important?

Here, we define customer lifetime value (CLV) as the total financial contribution from the current period into the future — that is, revenues minus costs — of a customer over his/her future lifetime with the company and therefore reflects the future profitability of the customer. Using CLV as a marketing metric, managers tend to place greater emphasis on customer service and long-term customer satisfaction for the right set of customers, rather than only attempting to maximize short-term sales.

For many years, firms did not focus on CLV due to the lack of empirical evidence on the impact of CLV on their revenues and profitability. Several of these firms focused on increasing revenue by continuously acquiring customers. However, many of these customers made only one purchase. Acquiring this type of customer was not an optimal strategy. Instead, firms should concentrate on identifying how much a customer would contribute to the firm's future profits. CLV does just this.

Customer Lifetime Value measures the worth of a customer to the firm. By calculating the CLV for all the customers, firms can rank order the customers on the basis of their contribution to the firm's profits. This can be the basis for formulating and implementing customer-specific strategies for maximizing each customer's lifetime profits and increasing each customer's lifetime duration. In other words, CLV helps the firm to treat each customer differently based on his or her contribution rather than treating all the customers same. The importance and relevance of CLV can be understood by the impact it makes on the following two issues:

(1) Calculating CLV helps the firm to know how much it can invest in retaining the customer so as to achieve a positive ROI. A firm has limited resources and ideally wants to invest in those customers who bring maximum return to the firm. This is possible only by knowing the cumulated cash flow of a customer over his or her entire lifetime with the company or the lifetime value of the customers.
(2) Once the firm has calculated the CLV of its customers, it can optimally allocate its limited resources to achieve a maximum return. The CLV framework is also the basis for selecting customers, selling the next best product/service to the customers, and deciding on the customer-specific communication strategies. CLV can be considered as the metric that guides the allocation of resources for ongoing marketing activities in a firm adopting a customer-centric approach.

It is important to point out that maximizing ROI and maximizing profitability can produce two very different results. Prior research has shown that optimal points of profitability and ROI are not the same (Kumar and Petersen, 2004). Further, before accepting maximizing ROI as an optimal strategy instead of maximizing profitability, it is important to realize that there can be significant consequences for over or under spending on marketing within your company. A recently published article has shown that, once all marketing contact strategies were optimized based on maximizing profitability, deviations from those strategies either 25% above or below marketing expenditures on acquisition and retention could have a severe impact on profitability (Thomas et al., 2004). By focusing on profit maximization, firms can attempt to sell as many products or services as possible to minimize the exposure of their customers to switch to competitors. Managers, therefore, should be careful before assuming their current system of maximizing ROI is going to be the best way to maximize profitability. It is possible that in some situations optimum levels of ROI and profitability are close in relationship to each other, but there can be situations where they are maximized at significantly different points.

While this is a radical thought being presented for managing customers, in the past, companies have used metrics that manage customer loyalty for managing customers. Traditionally, customer loyalty has been defined as a behavioral measure (Kumar and Shah, 2004). These measures include proportion of purchase (Cunningham, 1966), probability of purchase (Farley, 1964; Massey et al., 1970), probability of product repurchase (Lipstein, 1959; Kuehn, 1962), purchase frequency (Brody and Cunningham, 1968), repeat purchase behavior (Brown, 1952), purchase sequence (Kahn et al., 1986), and multiple aspects of purchase behavior (Ehrenberg, 1988; DuWors and Haines, 1990). The following section details the traditionally used metrics in managing customer loyalty in comparison with CLV, as a metric to manage customers. The rest of the survey details the shift from this traditional approach in customer management to the “CLV way” of managing customers.

3

Traditional Metrics for Managing Customer Loyalty

Each company is governed by a unique set of conditions, regional nuances and a strategic competitive environment. Therefore, marketers have access to various metrics for measuring and managing customer loyalty. A higher proportion of resources are assigned to customers who are expected to generate greater profits. Such customers are ranked by these metrics. Table 3.1 summarizes the popular metrics used by firms.

3.1 RFM Approach

Firms in some industry verticals maintain records of customers and keep track of when the last purchase was made and how many times each customer has purchased in a given time period, and so on. It is assumed that:

(1) Customers who had purchased *recently* were more likely to buy again versus customers who had not purchased in a while.
(2) Customers who had purchased *frequently* were more likely to buy again versus customers who had made just one or two purchases.

Table 3.1 Metrics used for measuring and managing customer loyalty.

Metric	Description
Recency, Frequency & Monetary Value (RFM) Approach	Recency refers to how long it has been since a customer last placed an order with the company. Frequency refers to how often a customer orders from the company in a certain period. Monetary value denotes the amount that a customer spends on an average transaction.
Past Customer Value (PCV)	PCV extrapolates the results of past transactions into the future. In this model, the value of a customer is determined based on the total contribution (toward profits) provided by the customer in the past.
Share-of-wallet (SOW)	SOW refers to the proportion of category value accounted for by a focal brand or a focal firm within its base of buyers. SOW estimation can be done at the individual customer level or at an aggregate level.

Source: Adapted from Kumar V., and W. J. Reinartz (2006), *Customer Relationship Management: A Databased Approach*. New York: John Wiley & Sons, Inc.

(3) Customers who had *spent the most money* in total were more likely to buy again.

Firms have tested the concept that past purchase behavior could predict future results. In a recent study, a firm ranked its customers based on the 3 attributes — recency, frequency, and monetary value. The customers who scored high on these attributes (bought most recently, most frequently, and spent the most money) were listed on top, and were considered to be the most responsive to future offers. Customers who had scored low on these attributes (not purchased for a while, had made few purchases, and had spent little money) were at the bottom of the list, and were considered to be the least responsive to future offers. Following this, the firm mailed catalogs to all the customers, and tracked how its best and worst customers responded to the mailings. They found a huge difference in response and sales between best and worst customers. Repeating this test many times, they found it worked every time. The best customers always had higher response rates than the group who ranked "worst." It worked so well that the firm decided to cut back on sending mail to people who were ranked "worst," and spent the money saved on mailing more often to their "best" customers. By performing this analysis, the firm increased its marketing efficiency and effectiveness by targeting to the most responsive, highest future value customers.

The Recency, Frequency, Monetary value (RFM) model works well in a high volume business. RFM helps organizations significantly not only in targeting valuable customers who have a very high chance of purchasing, but also in avoiding costly communications and campaigns to customers who have a lesser chance of purchasing. However, the RFM can only be applied to available historical customer data and not on data related to prospects.

3.2 Past Customer Value

Past Customer Value (PCV) is based on the assumption that past performance of a customer is an indicator of the future level of customer profitability. The future value of a customer is then extrapolated using each customer's PCV. Since these contributions are made at different points in time during the customer's tenure, all contributions have to be adjusted for time value of money. The cumulative contribution until the present period represents the PCV of a customer. PCV can be calculated as follows:

$$\text{Past Customer Value (PCV)} = \sum_{t=1}^{T} GC_{it} \times (1+r)^t \tag{3.1}$$

where,

i is the number representing the customer,
r is the applicable discount rate (for example, 12% per annum or 1% per month),
T is the number of time periods prior to the current period when the purchase was made,
GC_{it} is the Gross Contribution (GC) of transaction of the ith customer in time period t.

For example, consider Ryan, a customer of ABC Inc. His spending pattern for five months is provided in Table 3.2.

The Gross Contribution is calculated as:

$$\begin{aligned} \text{GC} &= \text{Purchase amount} \times 0.3 \\ \text{PCV Score} &= 6(1+0.01) + 9(1+0.01)^2 + 15(1+0.01)^3 \\ &\quad + 15(1+0.01)^4 + 240(1+0.01)^5 = 298.5468. \end{aligned}$$

Table 3.2 Spending pattern of a Ryan.

	Jan	Feb	March	April	May
$ Amount	800	50	50	30	20
GC	240	15	15	9	6

From the previous calculation, it can be seen that Ryan is worth $298.55 in the contribution margin, expressed in the NPV in May dollars. However, this model does not consider whether a customer is going to be active in the future. Further, it does not incorporate the expected cost of maintaining the customer relationship in the future.

3.3 Share-Of-Wallet

Share-of-wallet (SOW) measures the amount of money that the customer is spending on a particular brand versus other brands, thereby indicating brand preference. Since SOW is a good predictor of a customer's preference it could also be an indicator of loyalty to a firm's brand. Being a measurement of consumption behavior, it is presumed to be more reliable than attitudinal measurements such as satisfaction. The SOW is calculated at two levels:

Individual (Segment) Level: It is the value of sales (S) of the focal firm (i) to a buyer in a category divided by the size of wallet of the same customer in a given period of time.

$$\mathrm{SOW}_{\mathrm{individual}}(\%) = S_i / \sum_{i=1}^{I} S_i, \tag{3.2}$$

where,

S is the sales to the firm i,
$\sum_{i=1}^{I}$ is the sum of the sales across all firms that sell a category of products.

For instance, if an athlete spends on average $3500 per year on sports gear from firm ABC, out of a total of $5000 that he spends on sports gear that year across all firms, then, firm ABC's SOW for that athlete in that year is 70% for that year.

Aggregate Level: At the aggregate level, SOW denotes the proportion of category value accounted for by a focal brand or a focal firm within its base of buyers. In other words, it indicates the degree to which the customers of a focal firm satisfy their needs, in a category. The aggregate SOW is obtained by adding individual SOW across all customers and dividing it by the number of the firm's customers (Kumar and Reinartz, 2006).

3.4 Difference between CLV and Traditionally Used Metrics

Although RFM, PCV, and SOW are commonly used for computing a customer's future value, they suffer from several drawbacks (Reinartz and Kumar, 2003). A major shortcoming in the traditional metrics is that they are not forward-looking and hence do not consider whether a customer is going to be active in the future. They consider only the observed purchase behavior and extrapolate it to the future to arrive at the future profitability of a customer. Specifically, the drawbacks of the metrics include:

- RFM assumes that the recency, frequency, and monetary value of a customer's purchase explain the future value of the customer. It fails to account for other factors that help in predicting the customer's future purchase behavior and his or her worth to the firm. In addition, the weights given for R, F, and M greatly influence the computation of the worth of a customer.
- By definition, PCV does not account for future purchase behavior of customers. It also does not incorporate the expected cost of maintaining the customer in the future.
- SOW is based on responses from a representative sample of customers. It is unable to provide us with a clear indication of future revenues and profits that can be expected from a particular customer. This limits its use as a valuable input in designing customer-level marketing strategies.

Customer Lifetime Value (CLV), on the other hand, incorporates both the probability of a customer being active in the future and the marketing dollars to be spent to retain the customer. With specific reference to PCV, it is important to note that CLV is not a mere extrapolation of PCV. Rather CLV makes an informed decision as to when a customer buys, how much a customer buys and how much does it cost to make the sale. Therefore, a company expecting more competition would reduce the expected gross contribution per customer, reduce the probability of purchase or even adjust the discount factor in order to compute the CLV. As noted above, the purpose of calculating customer value is to design customer-level strategies so that firms can maximize ROI. For managing customers effectively, it is critical to know whether the customer will continue to purchase in the future, and estimate the expected value of profits the customer would bring into the firm.

After establishing that CLV is a conceptually better metric to manage customers, it is essential to know how CLV can be measured. The following section discusses how CLV can be measured, the approaches to measure CLV, the components of CLV, and the various models available for modeling CLV.

4

Measuring CLV

Customer lifetime value (CLV) is defined as the sum of cumulated cash flows — discounted using the Weighted Average Cost of Capital (WACC) — of a customer over his or her entire lifetime (three years in most cases) with the company. The reason for the time period being three years is due to two reasons — (a) product life-cycle and, (b) 80% of profit comes in three years (Gupta and Lehmann, 2005). The calculation of CLV is illustrated in Figure 4.1.

Customer Lifetime Value looks at a customer's value to the organization, based on predicted future costs and transactions. While traditional metrics do not take into account the probability of customer being active, CLV incorporates these aspects to give a better perspective for managers. By segmenting customers across these dimensions (future cost and current profitability), firms can better align marketing, sales, service, resources, and expenditures to optimize long-term customer value leading to long-term profitability. The CLV metric helps firms to address marketing issues with greater confidence. It guides the allocation of resources for ongoing marketing activities for a

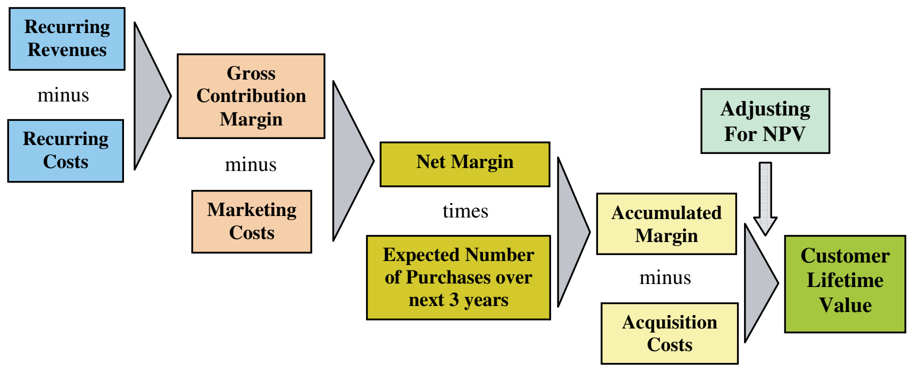

Fig. 4.1 Approach to CLV measurement.

customer-centric firm. The key issues with CLV are as follows (Kumar et al., 2004):

- How do firms decide which customers should be provided with preferential and sometimes personal treatment?
- Which customers should the firms interact with through inexpensive channels like the Internet or the touch tone phone, and which customer should the firms let go?
- How do firms decide the timing of an offering to a customer?
- How do firms decide which prospect will make a better customer in the future, and is therefore worthwhile to acquire now?
- After the customer makes a purchase, what kind of sales and service resources should the firm allocate, to conduct future business with that customer?
- How should firms monitor customer activity, in order to readjust the form and intensity of their marketing initiatives?

Managers want to have an idea of how the value of a client has evolved over time. In other words, CLV is a multi-period evaluation of a customer's value to the firm, and it assists managers to allocate resources optimally and develop customer-level marketing strategies. The lifetime value of a customer can be calculated by using either an aggregate level or at an individual level.

4.1 Aggregate Approach

According to this approach, the average lifetime value of a customer is derived from the lifetime value of a cohort or, segment or even a firm. Three approaches are available for computing the average CLV.

In the first approach, the sum of lifetime values of all the customers is calculated (Gupta et al., 2004). This value referred to as the customer equity (CE) of a firm and is calculated as follows:

$$\mathrm{CE} = \sum_{i=1}^{I} \sum_{t=1}^{T} \mathrm{CM}_{it} \left(\frac{1}{1+\delta} \right)^{t}, \tag{4.1}$$

where,

CE is the customer equity of the customer base (sum of individual lifetime values),
CM is the average gross contribution margin in time period t, (after taking into account marketing costs)
δ is the discount rate,
i is the customer index,
t is the time period,
T is the number of time periods for which CE is being estimated.

The information for contribution margin GC and the duration T are derived either from managerial judgment or from actual purchase data. The discount rate δ is a function of the cost of capital of the firm and can be obtained from the financial accounting function. The average CLV could then be calculated by dividing CE by the number of customers.

In the second approach, the average CLV of a customer is calculated from the lifetime value of a cohort or customer segment (Berger and Nasr, 1998; Kumar et al., 2004). The average CLV of a customer in the first cohort, or Cohort 1, can then be expressed as:

$$\text{Average CLV} = \sum_{t=0}^{T} \left[\frac{\mathrm{CM}}{(1+\delta)^{t}} r^{t} \right] - A, \tag{4.2}$$

where,

r is the rate of retention,
δ is the discount rate or the cost of capital for the firm,
t is the time period,
T is the number of time periods considered for estimating CE,
CM is the average gross contribution margin per customer in time period t, (after taking into account marketing costs)
A is the the average acquisition cost per customer.

This approach considers only the average gross contribution (GC), the average acquisition cost per customer (A), and the average marketing cost (M) per customer for calculating the CLV. However, in reality, the retention rate (r) for the cohort may vary over time. This is because customers may choose to discontinue the relationship with the firm at different points in time. Because of this, the retention probabilities would vary across customers. The need for varying retention rates are shown by Fader et al. (2005a,b). Therefore, the retention probabilities need to be factored in while calculating CE.

In the third approach, CE of the firm is first calculated as the sum of return on acquisition, return on retention, and return on add-on selling (Blattberg et al., 2001). Following this, average CLV can be calculated by dividing CE by the number of customers.

One important application of computing average CLV using one of the three aforementioned approaches is for the evaluation of competitor firms (Gupta and Lehmann, 2003; Kumar et al., 2004). In the absence of competitors' customer-level data, firms can deduce information from published financial reports about approximate gross contribution margin, marketing, and advertising spending by competing firms to arrive at reasonable estimates of the average CLV for a competitors' customers. The average CLV approach can also be used for evaluating the market value of the firm.

However, average CLV has limited use as a metric for the allocation of resources across customers. This is because the average CLV does not capture customer-level variations in CLV, which is the basis for developing customer-specific strategies. Hence, it is necessary to calculate the CLV of individual customers that will enable companies to design individual-level strategies.

4.2 Individual Approach

Customer lifetime value, at an individual level, is calculated as the sum of cumulated cash flows — discounted using the weighted average cost of capital (WACC) — of a customer over his or her entire lifetime with the company. It is a function of the predicted contribution margin, the propensity for a customer to continue in the relationship, and the marketing resources allocated to the customer. It is important to note that WACC is one of the measures that represent the discount factor used to compute CLV. There are other measures of discount factor (e.g., T-bills rate) that can be used to compute CLV. In its general form, CLV can be expressed as:

$$\mathrm{CLV}_i = \sum_{t=1}^{T} \frac{(\text{Future contribution margin}_{it} - \text{Future cost}_{it})}{(1+\delta)^t}, \qquad (4.3)$$

where,

i is the customer index,
t is the time index,
T is the number of time periods considered for estimating CLV,
δ is the discount rate.

Customer lifetime value has two components — future contribution margin and future costs — both adjusted for the time value of money. To calculate the future contribution from a customer in a non-contractual setting, a firm should know the probability that the customer continues to do business with the firm in future time periods or the probability of the customer being active, P(Active).

In a non-contractual setting, it may be useful for managers to ascertain the likelihood of a transaction by a particular customer. P(Active) is used in such circumstances. It refers to the probability that the customer continues to be active in a subsequent time period. Calculation of this probability at an individual level is essential for CLV calculation at an individual level. This is because each customer is likely to have different purchase patterns and inactive periods. Figure 4.2 illustrates this point.

Given the customer's past purchase behavior, one can predict the probability of an individual customer being active in subsequent time

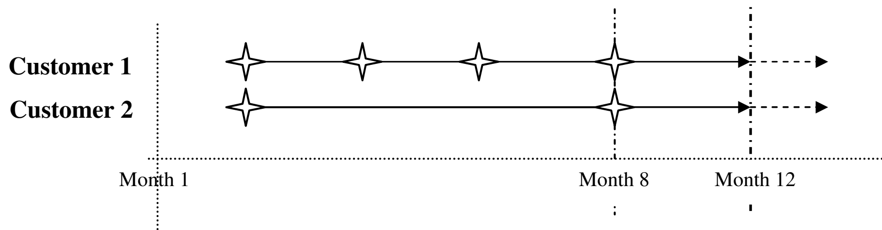

Fig. 4.2 Variation in inter-purchase time. *Source*: Kumar et al. (2004).

periods using a simple formula.

$$\mathrm{P(Active)} = (T/N)^n, \tag{4.4}$$

where,

n is the number of purchases in the observation period,
T is the time elapsed between acquisition and the most recent purchase, and
N is the time elapsed between acquisition and the period for which P(Active) needs to be determined.

In Figure 4.2, the "star" indicates a purchase made by a customer. Therefore, for Customers 1 and 2, the P(Active) for month 12 would be:

$$\text{P(Active) for Customer 1 in Month } 12 = (8/12)^4 = 0.197, \text{ where } n = 4.$$
$$\text{P(Active) for Customer 2 in Month } 12 = (8/12)^2 = 0.444, \text{ where } n = 2.$$

In the above example, it is interesting to note that a customer who has bought four times in the first eight months and has not bought in the last four months has a lower probability of buying in the 12th month, when compared to a customer who has bought only twice in the same period of eight months. Such an observation can be attributed to the budgetary constraints the customer might have, i.e., she/he may have spent their entire budget on prior purchases and therefore cannot afford any more purchases. It can also be due to the novelty effect wearing out, wherein the customer has frequented the store so much that she/he has less products and/or services to explore. However, advanced statistical methods are available to compute P(Active) (Reinartz and Kumar, 2003).

Now that we have looked at the two approaches to arrive at CLV, we need to take a closer look at the components of CLV. The following section explains the various components of CLV.

4.3 Components of CLV

The calculation of CLV includes determining the future contribution margin and future costs, both of which are adjusted for the time value of money. The calculation of future contribution margin and future costs are given below.

To calculate the future contribution from a customer in a non-contractual setting, firms should first determine the probability of the customer being active with the firm at future time periods. In other words, the firms should calculate the P(Active) of customers at period n. Then, the firms should ascertain the average monthly gross contribution (AMGC), which is calculated by deducting the average cost of goods sold from the average monthly revenue from a customer. This is obtained for all customers i and for the time-period t for which the lifetime value is being estimated. To arrive at the present value of the future contribution, the AMGC of the customers is adjusted with a discount rate d, for the number of time periods n. When the product of the P(Active) of customers at period n and the discount adjusted AMGC for all i customers are calculated for all future time periods x, we arrive at the net present value (NPV) of the expected gross contribution (EGC). This is empirically calculated as follows (Reinartz and Kumar, 2000, 2002):

$$\text{NPV of EGC}_{it} = \sum_{t=1}^{T} \text{P(Active)}_{it} \times \frac{\text{GC}_{it}}{(1+\delta)t}, \tag{4.5}$$

where,

GC_{it} is the average gross contribution margin for customer i in period, t based on all prior purchases,
i is the customer index,
t is the period for which NPV is being estimated,
T is the number of periods beyond t,

δ is the discount rate,
P $(\text{Active})_{it}$ is the probability that customer i is active in period t.

The cost component includes acquisition cost (A) and marketing cost (M) incurred at future time periods. The marketing costs at future time periods should be discounted with the appropriate discount rate (δ), in order to arrive at the present value of these costs. The discounted marketing costs (M) and the acquisition cost (A) are then subtracted from the NPV of EGC to arrive at the CLV of a customer. If the marketing costs are accounted at the beginning of a given time period and the gross contribution at the end of a time period, we can express CLV as:

$$\begin{aligned}\text{CLV of customer } i = {} & \sum_{t=1}^{T} \text{P}(\text{Active})_{it} \times \frac{\text{GC}_{it}}{(1+\delta)^t} \\ & - \sum_{t=1}^{T} M_{it} \times \left(\frac{1}{1+\delta}\right)^t - A_i, \end{aligned} \tag{4.6}$$

where,
GC_{it} is the average gross contribution margin for customer i in period, t based on all prior purchases,
i is the customer index,
t is the period for which NPV is being estimated,
T is the future time period,
δ is the discount rate,
P $(\text{Active})_{it}$ is the probability that customer i is active in period t,
M is the marketing costs of the firm,
A is the acquisition costs of the firm.

The components of the cost and future contribution margin that determines the calculation of CLV are explained as follows:

4.3.1 Average Monthly Gross Contribution

The average monthly gross contribution (AMGC) is the average monthly revenue obtained from a customer minus the average cost of goods sold. This is based on customer's past purchases as well as the increases in cost of the materials to purchase the goods/services.

4.3.2 Marketing Cost (M)

Marketing costs refer to the costs of programs that service customer accounts, increase the value of existing relationships such as loyalty or frequent flyer programs, and attempts to "win back" the lost customers. In general, it includes the development and retention costs. A major component of these costs is the cost of marketing through various channels of communication such as direct mail, e-mail or face-to-face interactions. The calculation of marketing costs becomes straightforward when firms decide the channel of contact, the number of contacts and the cost involved in contacting each customer. Such an exercise would help firms in developing customer-specific communication strategies.

4.3.3 Discount Rate (δ)

Since the value of money is not constant across time, and that the money received today is more valuable than the money received in future time periods, the gross contribution and marketing costs have to be discounted to compute the present value of money. This is done by dividing the cash flow in time-period i by $(1 + \delta)^i$, where d is the discount rate. The discount rate (δ) depends on the general rate of interest and is usually proportionate to the Treasury bill or the interest that banks pay on savings accounts. It can also vary across firms depending on the cost of capital incurred by the firm.

4.3.4 Time-Period (n)

The number of future time period (n) refers to the natural "lifetime" of the customers. The word *lifetime* has different connotations when pertaining to on–off purchases (e.g., house or other durables), versus frequently purchased goods (e.g., groceries). Another important aspect is the estimation of duration while making marketing decisions. For most businesses, it is reasonable to expect that the customers will return for a number of years (n); however, there are no strict guidelines to decide the value of n. For instance, a direct-marketer of general merchandise may consider a 4-year time span as a maximum; while in some cases she/he may consider only 2 years as a maximum while developing marketing decisions. The reason for this is that beyond a certain time-period any calculation and prediction may become difficult because of the presence of uncontrollable factors such as customer attrition and new competitors.

It is important to note that the effect of word-of-mouth (WOM) in generating additional business is not included as a component of the CLV model. It is computed separately and termed as Customer Referral Value (Kumar et al., 2007).

In calculating P(Active), there are other issues that have to be addressed by the managers. For instance, while using P(Active) it is assumed that a customer does not come back to the firm after choosing to discontinue the relationship with the firm. This approach, called "lost-for-good," is questionable because it systematically underestimates CLV (Rust et al., 2004). This can be overcome by using the "always-a-share" approach, which takes into account the possibility of a customer returning to the firm after a temporary dormancy in a relationship (Venkatesan and Kumar, 2004). By incorporating such an approach while predicting the frequency of a customer's purchases, managers will have a better view of future customer activity.

In estimating the probability of a customer being alive, the Pareto/NBD model is perhaps the most complete model that can be used. Originally developed by Schmittlein et al. (1987) and Schmittlein and Peterson (1994) (referred to as the SMC model), this model was later extended, to account for purchase volume (Schmittlein et al., 1987; Schmittlein and Peterson, 1994). Using only the information on customer transactions (such as the observation period, the number of purchases in that period, and the time at which the last purchase was made), this model computes the probability of a customer being alive at each point in time. Further, this model also considers the individual inter-purchase time of customers in predicting the probability of customer being alive. As mentioned earlier, this model was later extended to account for purchase volume. This model is ideally suited for situations in which there is non-contractual relationship, because in these situations, the firm does not observe directly how many "active" customers it has.

The SMC model describes the repeat-buying behavior in scenarios where customer dropout is unobserved. Here, the customer dropout is modeled using the Pareto (exponential-gamma mixture) timing model. The repeat-buying behavior is then modeled using the NBD (Poisson-gamma mixture) counting model. While this model was vastly useful in customer analysis, it posed challenges in empirical calculations, especially in parameter estimation. To reduce the computational challenges, a new model — the beta-geometric/NBD (BG/NBD) — was developed (Fader et al., 2005a). This new model shows how the parameters can be obtained easily even in Microsoft Excel, and how the two models yield very similar results.

Having understood the various components of CLV, let us see how the CLV model measures the variables independently. The following section illustrates one such method.

4.4 Model Measuring Variables Independently

In a recent research study, a generalized gamma distribution is used to model inter-purchase time and panel-data regression methodologies which are employed in modeling the contribution margin (Venkatesan and Kumar, 2004). Various supplier-specific factors (channel communication) and customer characteristics (involvement, switching costs, and previous behavior) are first identified as the antecedents of purchase frequency and contribution margin. Purchase frequency and contribution margin are then modeled separately using suitable models. These two models are, in turn, used together to predict CLV. The two models are provided below:

The likelihood function for purchase frequency is given as

$$L = \prod_{i=1}^{n} \prod_{j=1}^{J} \prod_{k=1}^{K} \Phi_{ijk} f_k(t_{ij}|\alpha_k, \lambda_{ik}, \gamma_k)^{c_{ij}} s_k(t_{ij}|\alpha_k, \lambda_{ik}, \gamma_k)^{(1-c_{ij})}, \quad (4.7)$$

where,

$f_k(t_{ij}|\alpha_{k,\lambda_{ik}}, \gamma_k)$ is the density function for the generalized gamma distribution (i.e., the probability of the jth purchase for customer i occurring at period t,

$s_k(t_{ij}|\alpha_{k,\lambda_{ik}}, \gamma_k)$ is the survival distribution of generalized gamma distribution,
c_{ij} is the censoring indicator, where $c_{ij} = 1$ if the jth inter-purchase time for the ith customer is not right-censored, and $c_{ij} = 0$ if the jth inter-purchase time for the ith customer is right-censored,
Φ_{ijk} is the probability of observation j for the ith customer belonging to subgroup k, and
$\alpha, \lambda_i, \gamma$ is the parameters of the generalized gamma distribution.

The independent variables in the contribution margin model are thus lagged contribution margin, lagged total quantity purchased, lagged firm size, industry category, and lagged total marketing efforts. Therefore, the contribution margin model is:

$$\begin{aligned}\Delta\mathrm{GC}_{i,t} &= \beta_0 + \beta_1\mathrm{CM}_{i,t-2} + \beta_2\mathrm{Quantity}_{i,t-1} + \beta_3\mathrm{Size}_{i,t-1} \\ &\quad + \Sigma_j\beta_j\mathrm{Industry}_j + \beta_4\mathrm{Totmark}_{i,t-1} + \mathrm{e}_{i,t},\end{aligned} \tag{4.8}$$

where,

$\Delta\mathrm{GC}_{i,t}$ is the difference in gross contribution margin from period $t - 1$ to period t for customer i, measured in dollars,
$\mathrm{Size}_{i,t-1}$ is the firm size for customer i in period $t - 1$, measured as number of employees,
Industry is the indicator variable for industry category of the customer firm,
$\mathrm{Totmark}_{i,t-1}$ is the total number of contacts made to customer i in period $t - 1$.

Customer lifetime value for a customer was calculated by combining these two models. For the implementation of this model it was assumed that correlation between the purchase frequency and the contribution margin is not significant. However, it is possible that how much a customer buys can be related to how often the customer buys. Therefore, a new model combining the two equations (Equations (4.9) and (4.10)) was proposed and the equation of CLV was derived as:

$$\mathrm{CLV}_{it} = \sum_{t=1}^{T_i} \frac{\mathrm{GC}_{it}}{(1+\delta)^t/\mathrm{frequency}_i} - \sum_{l=1}^{n} \frac{\sum_m \mathrm{MC}_{i,m,l}}{(1+r)^l}, \tag{4.9}$$

where,

CLV is the customer lifetime value,
$\mathrm{GC}_{i,t}$ is the gross contribution from customer i in purchase occasion t,
$\mathrm{MC}_{i,l,m}$ is the marketing cost, for customer i in communication channel m in time period l,
$\mathrm{MC}_{i,l,m} = c_{i,m,l}$ (unit marketing cost)$*$ $x_{i,m,l}$, (number of contacts)
$\mathrm{frequency}_i = 12/\mathrm{expint}_i$ (where, expint_i = expected interpurchase time for customer i),
r is the discount rate for money,
n is the number of years to forecast, and
T_i is number of purchases made by distributor i, until the end of the planning period.

The objective of relationship marketing with customer is to ensure that customers maintain future purchase behavior. The drivers for purchase frequency and contribution margin for the study can be viewed as supplier-specific factors and customer characteristics. They are explained below:

(1) Supplier-Specific Factors:
   a. Level of rich and standardized modes of communication.
   b. Intercontact time.
(2) Customer Characteristics:
   a. Bidirectional communication.
   b. Number of returns.
   c. Frequency of web-based contacts.

The drivers for contribution margin in the study were customer revenue and purchase quantity. A conceptual framework used to measure and maximize CLV is given in Figure 4.3. The CLV model described above can be employed to identify the responsiveness of customers to marketing communication through different channels of communication, which is the basis for optimal allocation of marketing resources across channels of contact for each customer so as to maximize his or her respective CLV. In addition to using the CLV framework for a resource allocation strategy, it can also be used for formulating other

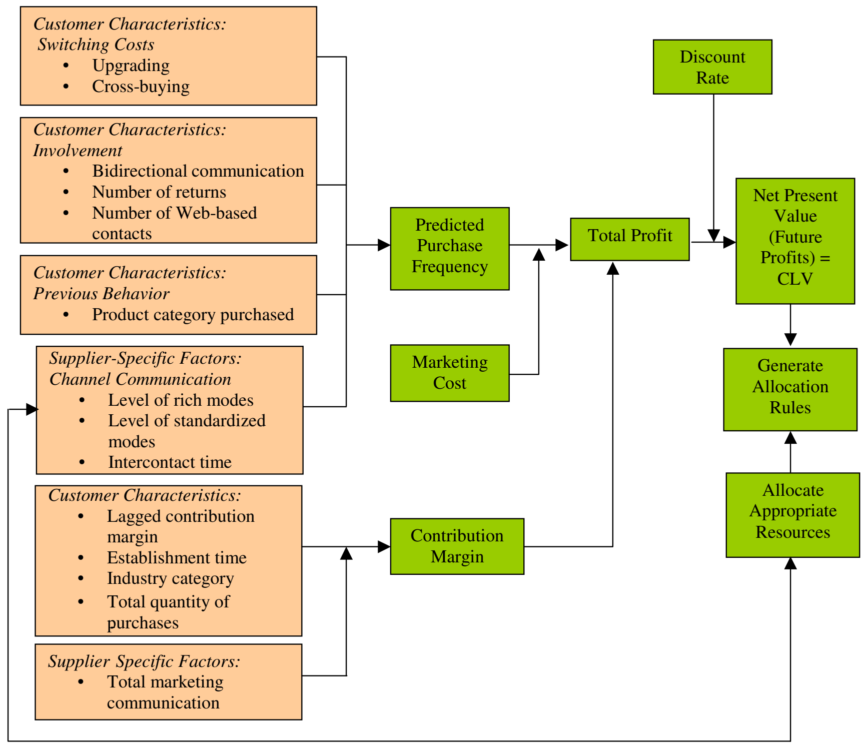

Fig. 4.3 A conceptual framework for measuring and using CLV.

customer-level strategies such as customer selection, purchase sequence analysis, and for targeting right customers for acquisition.

This CLV model measures variables independently and then integrates them together to derive CLV. However, such a modeling approach raises some key issues in modeling. These issues can be overcome when the model variables are measured simultaneously. The next section looks at one such model.

4.5 Model Measuring Variables Simultaneously

The CLV model is as follows:

$$\mathrm{CLV}_{it} = \underbrace{\sum_{t=1}^{T_i} \frac{\mathrm{GC}_{i,t}}{(1+r)^t/\mathrm{frequency}_i}}_{\text{PV of Gross Contribution}} - \underbrace{\sum_{l=1}^{n} \frac{\sum_m \mathrm{MC}_{i,m,l}}{(1+r)^l}}_{\text{PV of Marketing Cost}}, \qquad (4.10)$$

where,

CLV is the customer lifetime value for customer at time t,
$\mathrm{GC}_{i,t}$ is the gross contribution from customer i in purchase occasion t,
$\mathrm{MC}_{i,l,m}$ refers to Marketing cost, for customer i in communication channel m in time period l,
$\mathrm{MC}_{i,l,m} = c_{i,m,l}$ (unit marketing cost)* $x_{i,m,l}$ (number of contacts),
$\mathrm{frequency}_i = 12/\mathrm{expint}_i$ (where, expint_i = expected inter purchase time for customer i),
r is the discount rate for money,
n is the number of years to forecast, and
T_i is number of purchases made by customer i, until the end of the planning period.

In this model, $x_{i,m,l}$ gives the number of customer contacts made in a particular channel during a given time period. This includes in-person contacts initiated by the sales team, direct-mail, and telephone contacts. The marketing cost incurred for such contacts is given by $c_{i,m,l.}$. The frequency factor ($\mathrm{frequency}_i$) helps in forecasting the purchase frequency in the following years. The term $\mathrm{GC}_{i,t}$ predicts the gross contribution margin made by a customer in each future purchase occasion. Similarly, the future marketing cost ($\mathrm{MC}_{i,l,m}$) is also generated for each customer.

While this CLV model is a significant advancement beyond past customer value models, there are always ongoing efforts to uncover additional methods for improving the CLV measurement model. For example, there are two relevant issues that are related to calculating CLV and need to be addressed — Endogeneity and Heterogeneity. Without accounting for these statistical issues, the actual measurement of CLV can be biased.

Endogeneity is a statistical issue in the CLV model that relates directly to causation. This CLV model predicts the three parameters (frequency, MC, and GC) independently meaning that it does not take into account if it is current MC that leads to future GC or if it is potentially current GC that leads to future MC. This issue has a relatively straightforward solution and only requires that all three parameters are simultaneously obtained. This advanced model involves predicting three parameters that can be plugged into calculating CLV:

- Future customer activity (frequency).
- Future marketing costs (MC).
- Gross contribution margin from each customer (GC).

Heterogeneity is a statistical issue in the CLV model that relates directly to customer profiles. If we assume that different customers respond differently to marketing messages, it is not a good idea to have the same weights on all coefficients in the GC model relating to marketing communications. The solution to this problem is also fairly straightforward. If you allow regression weights to be different for each customer, you will get more accurate results for each customer.

There will always be continual improvements to the CLV model because of the nature of the availability of customer data and the business situation. However, having a reliable model like the one described earlier as a basis for measuring CLV is the key to establishing optimal marketing strategies. Knowing how to implement this model is also helpful to identify how CLV can be measured for different firms. There have been further developments in modeling CLV. The next sub-section briefly discusses the developments.

4.6 Alternate Approaches to Modeling CLV

This section briefly discusses the alternate approaches available to model CLV.

4.6.1 Brand-Switching Approach

This approach uses a CLV model, which incorporates customer-specific brand-switching matrices, although only for customers in the selected sample (Rust et al., 2004). This approach uses information about both the focal brand and the competing brands to model acquisition and retention of customers in the context of brand switching. Respondents in a selected sample provide information such as the brand purchased in the previous purchase occasion, the probability of purchasing different brands, and individual-specific CE driver ratings. The Markov switching matrix then models individual customers' probability of switching from one brand to another based on individual-level utilities. 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. Summation of expected contribution over a fixed time period after making adjustments for the time value of money (i.e., applying a discount factor) yields the CLV for the customer. The lifetime value, CLV_{ij} of customer i to brand j, is given as:

$$\mathrm{CLV}_{ij} = \sum_{t=0}^{T_{ij}} \frac{1}{(1+d_j)^t/f_i} V_{ijt} \times \pi_{ijt} \times B_{ijt}, \tag{4.11}$$

where,

T_{ij} is the number of purchases customer i makes during the specified time period,
d_j is the firm j's discount rate,
f_i is the average number of purchases customer i makes in a unit time, (e.g., per year)
V_{ijt} is the customer i's expected purchase volume of brand j in purchase t,
π_{ijt} is the expected contribution margin per unit of brand j from customer i in purchase t,
B_{ijt} is the probability that customer i buys brand j in purchase t.

Customer equity of firm j, CE_j is then calculated as:

$$\mathrm{CE}_j = \mathrm{mean}_i\ (\mathrm{CLV}_{ij}) \times \mathrm{POP}, \tag{4.12}$$

where,

mean_i is the average lifetime value for firm j's,
(CLV_{ij}) is the customers i across the sample,
POP is the total number of customers in the market across all the brands.

From the above equation, it is clear that individual-level CLVs are calculated only for the customers in the sample. The mean CLV calculated from the sample is taken as the average worth of a firm's customers.

4.6.2 Monte Carlo Simulation Algorithm

Recently, an alternative method was suggested to calculate the CLV, in which a company possesses a historical customer database, but does not have any information about customer purchases from competitors (Rust et al., forthcoming).

This model adopts the "always-a-share" approach in predicting future profitability. The "always-a-share" approach assumes that there is no dormancy in a customer–firm relationship and that customers never completely terminate their relationship with a firm. There is an assumption that customers will return to purchase from a firm after temporary dormancy. When customers return to the relationship they retain the memory about their prior relationship with the firm. Hence, in this approach, firms measure future profitability of a customer by predicting his purchase pattern over a prediction period, and do not predict when a customer will terminate his 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.

Given the information about customer behavior through certain time period, the profitability measures defined in this study are comprised of predictions of customer as well as firm behavior for a K-period time horizon. The predictions regarding customer behavior include, (a) the propensity for customer i to purchase in each future time period t and (b) the profit provided by customer i given purchase in future time period t. While the predictions of customer behavior capture the revenue aspect, marketing actions originated by the firm, such as number of sales calls or direct mail sent to a customer, capture the cost aspects, and need to be predicted for accurate CLV measurement. This research study proposes a single model framework that provides predictions of (a) customer purchase propensity, (b) customer profit, conditional on purchase, and (c) firm marketing actions, and also models the potential correlation among these factors.

Since the model proposed in this study is recursive and all equations are not feasible, a few steps were followed to estimate the model. First, the marketing action components were estimated and the corresponding residual was obtained. Then, the profit component using the predicted value of marketing actions was obtained from previous step as an independent variable. The corresponding residual was obtained. Factor analysis was implemented on the residuals and the factor coefficients were obtained. Using the factor coefficients and by maximizing the likelihood, the coefficients can be obtained. Then, the Monte Carlo simulation algorithm is applied for predicting future customer profitability based on the estimated model coefficients (Rust et al., forthcoming).

4.6.3 Customer Migration Model

The Customer Migration Model is another interesting CLV model that is suited for situations where customers adopt an "always-a-share" approach (Dwyer, 1997). Accordingly, customer behavior can be predicted based on historical probabilities of purchase depending on recency and the current recency state in which the customer is located (Berger and Nasr, 1998; Pfeifer and Carraway, 2000). Further generalizations included segmentation variables such as RFM and other demographic variables (Libai et al., 2002). In several situations, RFM is used as a segmentation tool by classifying as Low RFM and High RFM. The other segmentation approaches include SOW, customer life-cycle among others. In such a case, CE is expressed as:

$$\mathrm{CE} = \sum_{t=0}^{T} \frac{MM_t C_t P_t}{(1+d)^t}, \tag{4.13}$$

where,

MM_t is a matrix that contains the probabilities of customers moving from one segment to another at time t,
C_t is a vector containing the number of customers in each segment at time t, and
P_t is the profit from each segment at time t.

4.6.4 Stochastic Model

Using the internal data of a company, there are other models to estimate the CLV of a customer (Drèze and Bonfrer, 2001). One such approach defines CLV as a function of the interval of time between email contacts sent to a customer. It expresses CLV as:

$$\mathrm{CLV}_\tau = \frac{(1+d)^\tau}{(1+d)^\tau - p(\tau)} A(\tau), \tag{4.14}$$

where,

τ is a fixed time interval between contacts,
$A(\tau)$ is the expected surplus from communications following the interval, and
$p(\tau)$ is the probability of retention given that interval.

Using the data from a firm in the entertainment industry, this model estimates the relationship between the time interval and CLV. The objective is to find the optimal time interval time for permission-based emails to a customer base.

Apart from internal data, survey data can also be used to estimate the CE of a firm (Rust et al., 2000, 2004). Such an approach does not require complicated modeling techniques and complex databases. Further, this might be beneficial to small firms that may not have the necessary resources to invest in database technologies. Additionally, the model allows managers to identify which sub-drivers of CE are the most important and where the resource allocation of efforts should be focused. However, the demerit of such a model is that it assumes purchase volume and interpurchase time to be exogenous, and that it might be difficult to update frequently (Villanueva and Hanssens, 2007).

4.6.5 Probabilistic Model

In a recent study, a model has been developed that links RFM directly to CLV (Fader et al., 2005b). In other words, rather than including RFM variables in a scoring model simply because of their predictive performance as explanatory variables, the model links the observed measures to the latent traits. The model further shows that no other information about customer behavior is required to implement the model. Using iso-value curves (which enable the grouping of individual customers who have different purchasing histories but similar future valuations), the model identifies an excellent way to summarize and evaluate the CLV for an entire customer base. The only customer level information this model uses is the past purchase behavior of the customer, captured by recency and frequency. For calculating the expected lifetime value of a customer it is essential to determine the — (a) customer's value over time, (b) customer's churn probability over time and, (c) the discount factor for net present value (Fader et al., 2005b; Rosset et al., 2003). The formula for calculating CLV is given as:

$$E(\mathrm{CLV}) = \int_0^{\infty} E[v(t)]S(t)d(t)dt, \tag{4.15}$$

where,

$E[v(t)]$ is the expected value (or net cash flow) of the customer at time t (if active)
$S(t)$ is the probability that the customer has remained active to at least time t
$d(t)$ is the discount factor that reflects the present value of money received at time t.

While this formula is attractive and straightforward, the challenge lies in estimating the $v(t)$ and $S(t)$ components in a reasonable way. This study considered an online music site, CDNOW, which had a customer dataset of 23,560 over a 78-week observation period. In the observed period, 11,506 customers made at least one repeat purchase. The study integrated the customer characteristics along with the iso-value curves to derive the overall CLV for the customer base.

The customers who made repeat purchases (11,506 customers), were sorted on RFM characteristics. The sorting was done in the following manner:

- First, the customers were sorted in descending order on recency. Following this, the customers in the top tercile (most recent) were coded as R = 3, customers in the second tercile as R = 2, and customers in the last tercile (least recent) as R = 1.
- Then, the entire list was sorted in descending order of frequency, and coded as F = 3 for customers in the top tercile

(highest number of transactions), F = 2 for customers in the second tercile, and F = 3 for customers in last the tercile (least number of transactions).
- Finally, the customer list was sorted in descending order on average transaction value, and coded as M = 3 for customers in the top tercile (highest average transaction value), and so on.

Further, the customers who made no repeat purchases (12,054 customers) were coded as R = F = M = 0. The RFM-based code classification resulted in 28 distinct groups. The total CLV for the 28 groups and the size of each RFM group were compiled into a table for further analysis. The analysis revealed the following:

- The R = F = M = 0 cell revealed a significant learning. Although each customer in that cell has a small CLV value (an average expected lifetime value of $4.40 beyond Week 78 for someone who made his/her initial purchase), when it was extended to a large group of customers, this was a very high value. While it could be easily assumed that after a year and a half of inactivity, a customer has dropped out of the relationship with the firm, this cell revealed that these very light buyers collectively constitute approximately 5% of the total future value of the entire cohort, which is greater than most of the 27 other RFM cells.
- When the recency — frequency combination associated with each level of the monetary value dimension is considered, the study finds consistent evidence that high-frequency/low recency customers are less valuable than those with lower frequency.
- As expected, the high-frequency/high-recency/high-monetary value customers had the greatest CLV. It represents an average net present value of $435 per customer — approximately 38% of the future value of the entire cohort.

- When the cohort is considered as a whole, the average CLV is approximately $47 per customer, making the entire group of 23,560 customers worth slightly more than $1.1 million.
- When the average CLV for each RFM tercile is considered, the greatest variability in CLV was found in the recency dimension, followed closely by the frequency dimension. The least variation was observed in the monetary value dimension. Such a finding falls in line with the popular view that recency is usually a more powerful discriminator than frequency or monetary value.

With these findings, this model not only helps translate prior customer behavior into likely future trends, but also provides a cleaner image of the patterns using the iso-value curves. From a managerial standpoint, this model requires only the customer's RFM characteristics, which is readily obtainable. The use of iso-value curves can further help guide managerial decision making by providing accurate quantitative benchmarks to gauge the return on investment for programs that companies use to develop and manage their portfolios of customers.

Based on the type and amount of data available, knowledge, time, and resources available as well as the intended use of the CLV measure will guide the choice of the model. Now that we have computed CLV and looked at the developments made in modeling CLV, it will be interesting to know about the drivers of CLV. These factors impact the computation of CLV and ultimately determine how customers are managed. The following section discusses the drivers of CLV.

It is important to note that both deterministic and probabilistic models are used to estimate CLV. The model developed by Fader et al. (2005a,b) belongs to the class of probabilistic models. Even among the class of probabilistic models, some models use certain drivers to predict CLV. In the next section, we will discuss the typical drivers of CLV.

5

Drivers of CLV

Introducing customer loyalty has been the prime focus for organizations in order to develop customer relationship. For effective implementation of this exercise, a better understanding of the factors determining customer–firm relationship is essential. As already discussed, loyalty is not a direct measure of profitability, since all loyal customers are not always profitable. The factors that drive profitable customer loyalty are classified into exchange characteristics and customer heterogeneity. The profitable duration of customer–firm relationship depends, differentially, on the exchange characteristics at time t and on customer heterogeneity. The profitable lifetime duration can be expressed as (Kumar and Reinartz, 2006):

$$\begin{aligned}&\text{Profitable Lifetime Duration}_i\\&\qquad = f(\text{Exchange Characteristics}_{it},\ \text{Customer Heterogeneity}).\end{aligned}$$

Exchange characteristics encompass the set of variables that define and describe relationship activities in the broadest sense. It includes the set of variables that specify distinctly relationship activities.

The variables vary for different industries. Some common exchange characteristics are:

- The average monthly spending level over a given period (customer spending level).
- The number of different products/categories purchased (cross-buying behavior).
- The level of customer purchases within a single category (focused buying).
- The average number of days between purchases (average inter-purchase time).
- The amount of customer returns.
- The level of usage of loyalty programs offered by the company.
- The number of mailing efforts by the firm.

In case of a B2C firm, customer heterogeneity includes variables such as age, gender, spatial income, and physical location of the customers. In case of a B2B firm, customer heterogeneity includes variables such as industry, annual revenue and location of the business.

A clear understanding of these factors, which forms the basis for strategy development, is thus essential for building customer loyalty.

Even as CLV is widely gaining acceptance as a metric to acquire, grow, and retain the right customers, firms face certain challenges with existing models to calculate CLV. The challenge that most marketing managers faced was to achieve convergence between marketing actions (e.g., contacts across various channels) and CRM. Once the computation of CLV is completed, firms must look forward to maximize it so as to reap the full benefits of the metric. The following section discusses the various strategies that firms can use to maximize customer lifetime value.

6

How Can CLV Measure be Used for Developing Customer-Centric Strategies?

In recent years, managers have tried to measure and maximize the lifetime value of each and every customer. If a company truly understood each customer's lifetime value, it could maximize its own value by increasing the number, scope and duration of value-creating relationships. To do this, managers would have to determine how much revenue each customer would generate in the future and subtract the expected costs of acquiring, serving and keeping the customer. Some cutting edge marketing strategies available for maximizing CLV are discussed in this section (Kumar and Petersen, 2005).

6.1 Customer Selection

The old school of thought is that retaining more customers will increase the overall profitability. Traditional metrics like RFM, Past Customer Value (PCV) and Share-Of-Wallet (SOW) support this view. However, the CLV approach suggests that the contribution of most of the customers is not significant when compared to the cost incurred by firm in retaining them, thereby depleting the firm's overall profitability.

Therefore, customer selection becomes an important customer-centric strategy for a firm.

There is no doubt that the cost of retaining a customer is lower than that incurred for acquiring a new customer. In the past, firms have found that all customers are not profitable customers. While one set of customers of the firm do not contribute to the overall profitability of the firm, and cost more to be retained, there is another set of customers who not only add value to firms by increasing the revenues but also by helping the firm attract other customers through positive word-of-mouth. Therefore, it becomes obvious that the former set of customers is not worth pursuing, and the latter set of customers should be retained so that firms can maximize their revenues.

The decision of which customer to retain can be answered by CLV. In the previous section, we discussed that different firms have different drivers of profitability and that the lifetime value of customers also differs across different firms. Thus, the firm has to determine the CLV of customers and the drivers of profitability that are applicable and suitable for them. Some of the drivers that are significant predictors of profitable lifetime duration for most firms include past purchase amounts, extent of cross-buying, and depth of buying in a single category. For example, in the past, many retail stores such as Gap and Polo Ralph Lauren have focused on marketing to customers who spend large amounts of revenue on the firm. It is more important to choose customers who bring the most value to the firm, as compared to customers who are bringing in high revenues. It is important for retail stores as well as other firms to identify the drivers of high-value customers, not just high-revenue customers, when they are making an effort to choose which customers they target. This, however does not imply denying business to any customer who walks in; it just means that they ensure that proper incentives have to be provided to those customers who are most likely to be profitable.

Once the customer values and drivers have been identified, a firm can select those customers with positive lifetime values, and allocate marketing resources and customized marketing campaigns directed at each customer. This is especially important in cases where a firm is constrained by a limited budget and has the resources to contact only

Table 6.1 Profits generated using customer selection strategy by different metrics.

% of Cohort (Selected from top)		Using the first 30 months of data to predict the next 18 months of purchase behavior			
		Customer lifetime value	Share-of-wallet	RFM	PCV
5	Gross profit	146,862	76,766	92,609	131,735
	Variable costs	1,270	620	1,051	950
	Net profit	**145,592**	**76,146**	**91,558**	**130,785**
10	Gross profit	79,699	31,618	55,667	72,686
	Variable costs	751	588	775	794
	Net Profit	**78,948**	**31,030**	**54,892**	**71,892**
15	Gross profit	58,370	17,813	36,370	52,591
	Variable costs	690	512	632	809
	Net profit	**57,680**	**17,301**	**35,738**	**51,782**

Source: Data from a catalog retailer.

a percentage of its customer base (Kumar and Petersen, 2005). By selecting the right customers based on their value potential, firms can allocate marketing resources to these high-valued customers.

An empirical illustration (Table 6.1) shows how customer lifetime metrics outperform traditional metrics after the customer selection strategy is applied. Customers selected represented the top 5%, 10%, and 15% of cohorts and the data for last 30 months was used to predict the customer buying behavior for next 18 months.

It was observed from the study that the value of net profits increased when the customer lifetime value (CLV) metrics is applied. The profits increased significantly when the right customers were chosen. The study also suggests that CLV metrics are better than traditionally used metrics for all the cohorts of customers selected. For the 5% cohort of customers the net profit obtained by using metric CLV was double the value of net profit obtained by SOW metrics, and one and a half times the value of net profit obtained through RFM. The value of net profit under PCV metric was high but not as high when compared to CLV. Similar results were observed for 10% and 15% cohorts whereas the value of net profits in 10% cohorts under SOW was half that of CLV; it was one-third for 15% cohorts. Therefore, selecting the right customer is an effective strategy for improving net profits when CLV metrics are applied.

6.2 Customer Segmentation

Customer segmentation procedures include deciding on what data will be collected, how it will be gathered, how it will be integrated from various sources, the methods of data analysis for segmentation, establishing effective communication among relevant business units (such as marketing and customer service) about the segmentation, and implementing applications to effectively deal with the data and to respond to the information it provides.

Segmenting customers would help firms design effective marketing plans for customers. While traditional segmentation focused on identifying customer groups based on demographics and attributes such as attitude and psychological profiles, CLV undertakes a value-based approach. Value-based segmentation looks at groups of customers in terms of the revenue they generate and the costs of establishing and maintaining relationships with them. Figure 6.1 looks at customer segmentation based on profitability and customer longevity.

The matrix suggests how customers can be sorted based on customer longevity and customer profitability for the firm. While there may be long-standing customers who are only marginally profitable, there also may be short-term customers who are highly profitable. The four quadrants of the matrix illustrate the different segments of customers segmented on the basis of value and how they can be managed to maximize profitability.

True Friends are the most valuable customers. They fit in well with what the company has to offer. They are also steady purchasers, buying regularly (but not intensively) over time. They offer the highest profit potential for the firm. While managing true friends, firms should indulge in consistent, yet intermittently spaced communication. Firms should concentrate on finding ways to bring out the true friends' feelings of loyalty, and strive to achieve attitudinal and behavioral loyalty.

Butterflies are customers who offer high profitability for the firm even though they stay only for a short term. These customers are profitable and transient. They enjoy finding out the best deals, and avoid building a stable relationship with any single provider. A classic mistake made in managing these accounts is continuing to invest in them

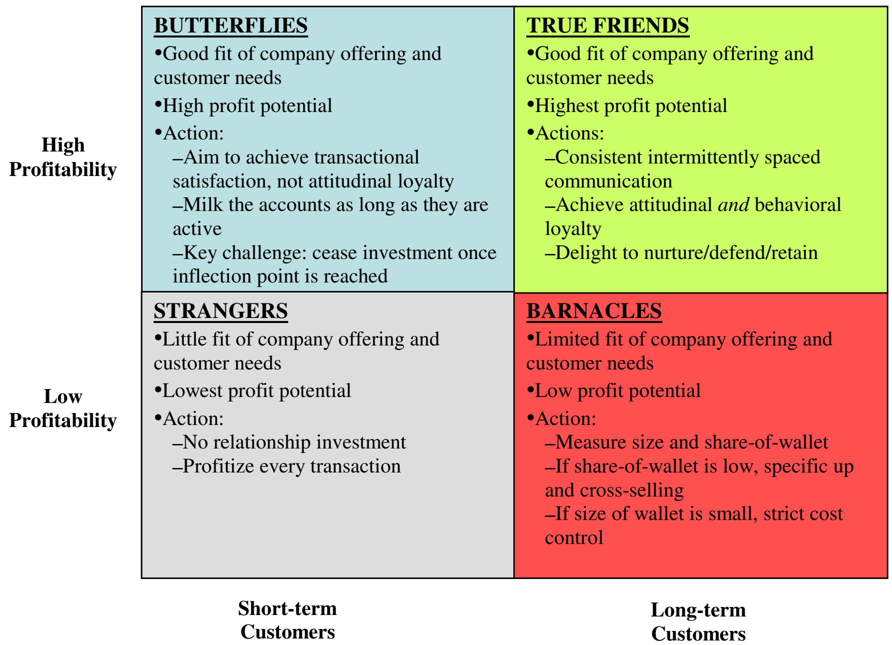

Fig. 6.1 Managing customer segment.

after their activity stops. Hence, to manage this type of customers, firms should aim to achieve transactional satisfaction, and *not* attitudinal loyalty. In other words, the managers should look for ways to derive as much revenue as possible while they can and find the right moment to cease investing in them.

Barnacles are those customers who, in spite of being long-term customers, offer low profitability for the firm. They are a limited fit for the company and provide low profit potential. They do not generate satisfactory return on investments because the size and volume of transactions are too low. Like barnacles on the hull of a cargo ship, they only create additional drag. However, when properly managed, they can sometimes become profitable. To manage such customers, firms should determine whether the problem is a small wallet or a small SOW. If the SOW is found to be low, specific up-selling and cross-selling can be done to extract profitability. However, if the SOW is small, then, strict cost control measures can reduce the loss for the firm.

Strangers, as the name suggests, are the least profitable customers for the firm. They fit in poorly with the company offerings. To manage these customers, the key is to identify them early and refrain from making any relationship investment. These customers have no loyalty toward the firm and bring in no profits. Hence, the firm's aim should be to extract maximum profit from every transaction with these customers (Reinartz and Kumar, 2002).

Because of effective customer segmentation firms have increased their revenue as a result of their increased ability to meet customer's needs. Customer segmentation has resulted in an increased number of customers firms are targeting, sales per customer, customer profitability, and lifetime value of customers. It is to be noted here that while the chance of misclassification of customers between the four quadrants does exist, the model provides sufficient scope for regular reevaluation of customers and constant updating of customer segmentation status. The updating of the four customer quadrants should be based on the purchase cycle of the products/services.

6.3 Optimal Resource Allocation

Optimal resource allocation is a process that determines which customer to target in order to assign the available marketing resources so that they produce the maximum possible profits in the minimum possible time. This strategy aims to maximize profits by reducing the cost incurred. Often firms have limited marketing resources for a larger customer base and therefore are confronted with a problem of allocation of resources. Ideally, firms should only invest in customers who add more value to the firm. Most of the time they end up investing more in customers who are easy to acquire but may or may not add value to firm.

Traditionally, firms had adopted the "duration of association approach" to segment its customers into high and low value groups. In other words, all longer duration customers were classified as high value customers and shorter duration customers were classified as low value customers. This approach was working for the firms, since the average profits from long standing customers were substantially higher than the average profits from the recent customers. But, when CLV was adopted and carried out for each customer, it was discovered that there is a significant number of customers among the short duration customers who had been misclassified as low value customers. Table 6.1 shows the average profits delivered by customers in all the four different cells.

From Table 6.2, firms observed that some profitable customers from Cell I were ignored whereas, some customers in Cell III were over invested in. Firms realized the misallocation of resources and optimized their resources to proper channels. Firms also realized that not only is the average profit higher when the duration is longer, it also markedly higher when the CLV of customers are high. Therefore, the firms will be more interested to move customers from Cell III to Cell II so that they ensure a higher profit margin and optimally allocate resources between the customers.

The firm traditionally followed a SOW approach to classify its customers. As explained earlier, SOW is classified as the percentage of the dollar value of the customer's entire wallet that is spent with the focal firm. The firm would invest a greater amount of resources on customers classified as high SOW than the customers classified as low SOW. The CLV computation across four cells reads as: high SOW–high CLV, high SOW–low CLV, low SOW–high CLV and, low SOW–low CLV.

Table 6.2 Customer value versus duration of association for a B2B vendor.

	Shorter Duration	Longer Duration
High Customer Value	**Cell II** N = 92 Average Profit =$52,976	**Cell IV** N = 72 Average Profit =$302,542
Low Customer Value	**Cell I** N = 78 Average Profit = $1,387	**Cell III** N = 82 Average Profit = $1,245
	Average profit of shorter duration customers is $29,305	**Average profit of longer duration customers is $142,111**

The CLV framework helps firms to allocate their resources to most profitable customers and also helps in how to invest on those customers. By using the optimal resource allocation strategy, as shown in Figure 6.2, marketers can decide on allocation of limited marketing resources across all the customers/distributors (Kumar and Reinartz, 2006).

In this matrix framework, customers are grouped based on their SOW and value to the firm. Accordingly, Cell I consists of customers who are of little value to the firm and have a low SOW. Firms should avoid investing in these customers to prevent loss. Cell II consists of customers who are of high value to the firm but have a low SOW. Firms should consider the conversion strategy with these customers by increasing their SOW. Cell III consists of those customers who offer a low customer value in spite of a high SOW. The reason for high

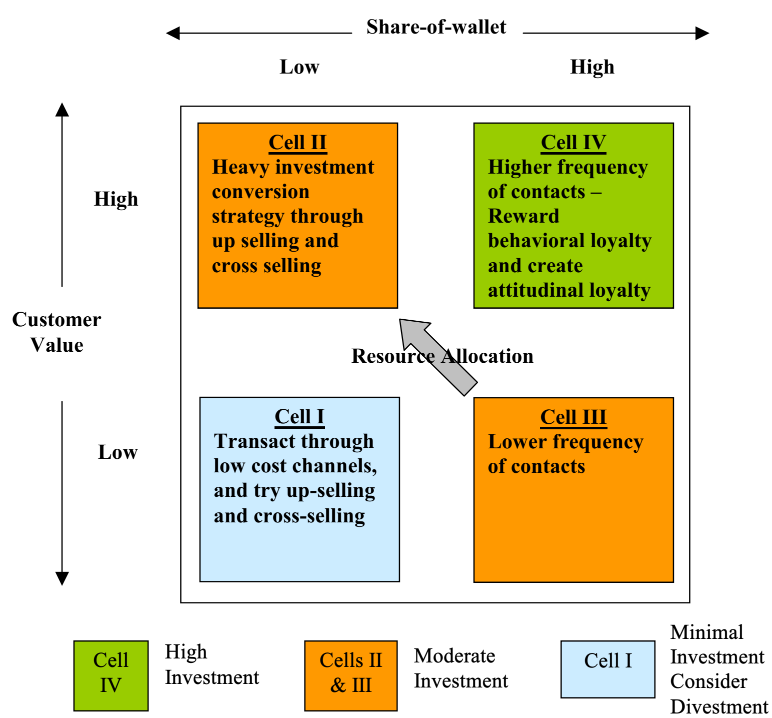

Fig. 6.2 Optimal resource allocation strategy.

SOW–low customer value may be because of a small size of the wallet and thereby not enough resources to spend. Cell IV consists of customers who have a high SOW and offer high customer value. They are prime targets for customer loyalty programs and an area of high investment for the firms. Firms should consider allocating resources from Cell III to Cell II with a view to increase the SOW of the customers in Cell II.

The optimal resource allocation strategy enables the firm to take specific marketing actions for a larger set of customers/distributors, for a given budget. It provides the firm with the framework to assess return on its marketing investments and hence bring accountability to marketing actions. It also provides early indications to the firm about a customer's or distributor's transition through various phases of the life-cycle (exploration, evaluation, maturity, and decline). The resource allocation strategy provides a basis for evaluating the potential benefits of CRM implementations in organizations and lends accountability for strategies geared toward managing customer assets.

The average frequencies with which face-to-face sales contact and other impersonal channels of communication (direct mail/telesales) were carried out on customers in each cell changed according to the CLV realized from each customer.

Table 6.3 outlines the original resource allocation and the optimal resource allocation recommended. A 10% decrease in overall costs and a 6% increase in overall profits were realized by switching over to the optimal frequencies for face-to-face meetings and direct mail/telesales in each of the four cells. Optimizing the mix and frequency of the various channels of distribution to suit every individual customer is likely to result in higher profitability.

A recent study showed that a resource allocation strategy that maximizes CLV resulted in an 83% increase in profits (Venkatesan and Kumar, 2004). For each customer the resource allocation level is maintained for the most recent year and CLV is calculated over a period of three years. Based on previous resource allocation strategy the present value of future profits was estimated to be $24 million, whereas, after adopting resource allocation strategy, which maximizes CLV, the present value of future profits was expected to be $44 million. The total

Table 6.3 Reallocation of resources.

Customer value	Share of investment: Low	Share of investment: High
High	*Face to Face Meetings*: • Currently meets once every six months. • Optimal meeting frequency is once every three months. *Direct Mail/Telesales*: • Current Interval is 30 days. • Optimal interval is 16 days.	*Face to Face Meetings*: • Currently meets once every four months. • Optimal meeting frequency is once every two months. *Direct Mail/Telesales*: • Current Interval is 14 days. • Optimal interval is 7 days.
Low	*Face to Face Meetings*: • Currently meets once every six months. • Optimal meeting frequency is once every 12 months. *Direct Mail/Telesales*: • Current Interval is 30 days. • Optimal interval is 66 days.	*Face to Face Meetings*: • Currently meets once every four months. • Optimal meeting frequency is once every six months. *Direct Mail/Telesales*: • Current Interval is 14 days. • Optimal Interval is 28 days.

cost of communication based on current strategy was $716,188 whereas, after adopting the resource allocation strategy used for maximizing CLV, the cost of communication increased to $1 million. By mobilizing the resources in the right direction the profits increased by $20 million and the firm improved its profits by increasing cost 48%. The study was done on a sample of 216 customers and it was suggested that if the firm adopts similar resource allocation strategies for the entire customer base, it can increase the revenues by $1 billion.

The results from this study highlighted the importance of firms' considering individual customers' responsiveness to marketing communication as well as the costs involved across various channels of communication when making resource allocation decisions. Through the analyses, a potential for substantial improvement in CLV through appropriate design of marketing contacts across various channels was identified. Using Genetic Algorithm, which is a parallel search algorithm, we can find the optimal point quicker. Therefore, when firms design resource allocation rules, they can realize the increase in profits by incorporating the differences in individual customer responsiveness to various channels of communication and the potential value provided by the customer.

The optimal resource allocation strategy enables the firm to take specific marketing actions for a larger set of customers/distributors, for a given budget. It provides the firm with the framework to assess return on its marketing investments and hence bring accountability to marketing actions. It also provides the firm with early indications about a customer's or distributor's transition through various phases of the life-cycle (exploration, evaluation, maturity, and decline). The resource allocation strategy provides a basis for evaluating the potential benefits of CRM implementations in organizations and lends accountability for strategies geared toward managing customer assets.

6.4 Purchase Sequence Analysis

Purchase sequence analysis pertains to a subsequent purchase of a product(s) given a previous set of purchases. For instance, buying an extended warranty is more likely to follow (in that specific sequential order) the purchase of a TV or any other electric appliances. In addition, most companies offer an array of products. There is a possibility that a customer who has just bought a product will not to buy the same product in the near future. It would be useful for a firm to predict the relative probabilities of different product categories being bought at different times from a given firm, given the varying purchase patterns of each customer. This would enable firms to choose customers who are more likely to buy and send them appropriate sales and promotion messages to those customers.

The traditional model used to predict purchase sequence involves two steps:

(1) Estimating the probability that a customer will make a purchase at a particular time.
(2) Estimating the probability that a customer will purchase a particular product at the predicted purchase time.

Therefore, the final probability of a customer purchasing a particular product at a predicted time is the multiplied result of these two probabilities. The basic theory behind this framework is that customers tend to purchase goods and/or services in a similar order and timing as other customers. This can occur because of several reasons. Usually, a natural order of purchasing is necessary for the customer to get the best use of the products. For example, if a customer purchases an application server, application server software, followed by a database server, it is likely that the next product he will need is database server software. Therefore, by following the trend of purchases, a company can make proper inferences about what a customer is likely to buy next given the logical path of purchase. However, looking at the trend of customer behaviors in the past will only have limited predictive accuracy into the future. There may be an even more accurate way of measuring purchase sequence and timing.

Consumers also seem to follow other patterns of purchasing. This may be the consequence of observational learning or through word-of-mouth. In case of observational learning, consumers look at the purchase patterns of other consumers and, rather than using their own personal/private information about a consumption decision, choose to follow the purchasing decision patterns of previous consumers. Most of the time, this occurs because finding and developing your own personal database of product information is time consuming. Allowing other consumers you trust to help you make decisions by observing their purchase patterns can save time and resources. Likewise, the effect of word-of-mouth is similar to that of observational learning, except that there is communication between the customer and potential consumer causing the consumer to make a purchase decision based on the external information passed along via conversation rather than using his/her own private information. In either case, the consumer chooses to purchase a product or a series of products in a similar sequence as a past customer, allowing the firm to model behavior and predict the likelihood of purchase timing and sequence.

The probability that a customer will choose to buy a particular product is assumed to be a function of various variables like demographics and past buying behavior. Managers use these variables in order of their relative importance by looking at a sample of customers. At the end of this exercise, managers get a series of probabilities that tell them which customers are most likely to buy a particular product and which products a particular customer is most likely to buy. After estimating these probabilities, managers try to estimate the probability that a customer will make a purchase at a given time. This probability function is based on an average interval between purchases for all customers in the sample and how often marketing materials (number of times they are contacted) have been sent to each person. This helps managers to estimate how many times (for e.g., which months) each customer is most likely to buy any of the firm's products. The joint probability for each customer's future purchase behavior is calculated by multiplying the probabilities (which product the customer will buy and when the next purchase will be).

Managers will get a three dimensional probability cube from these joint probabilities ("The Customer Probability Cube"). They can use the cube in various ways, like identifying what products each customer will buy over a period of time and when the purchase is most likely to happen. They can also identify the customers who are most likely to buy each product and the times when the product will be in demand.

Figure 6.3 shows how managers use the probability cube to predict what products customers will buy and when. Managers use the

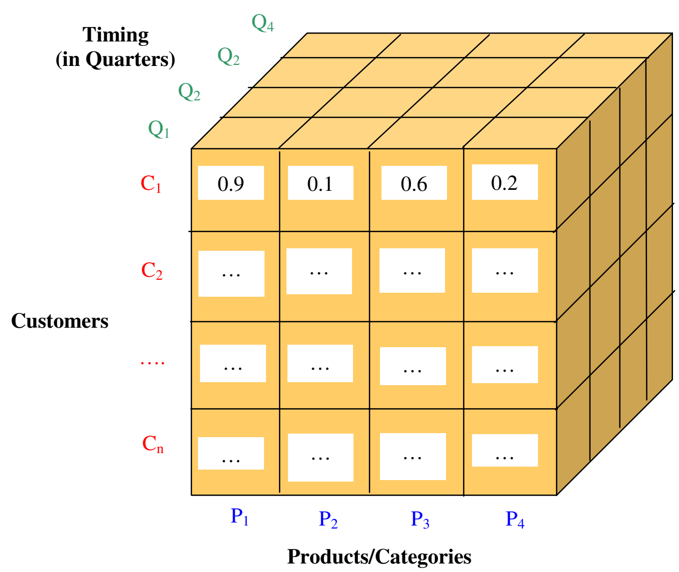

Fig. 6.3 Customer probability cube.

probability cube to determine the probabilities of purchase along three dimensions: customers, products, and timing. The cube in Figure 6.3 shows a company that sells four products. The numbered cells indicate that there is a 90% chance that customer 1 will buy product 1 in the first quarter, a 10% chance that he/she will buy product 2 in the first quarter, a 60% chance that he/she will buy product 3 in the first quarter and a 20% chance that he/she will buy product 4 in the first-quarter. From the figure, it can be observed that the probabilities of purchase do not add up to 1. This is because the product categories are not mutually exclusive. This cube also allows the managers to identify which customers are most likely to buy which product(s) in quarter 1, as well as the product(s) that each customer is likely to buy in the other three quarters (Kumar et al., 2006).

To illustrate the power of the combined estimation of the choice and the purchase timing model, let us assume that we are observing purchase behavior data for a period of n years. Customers can buy any product j from a list of J products at any time t in a period of n years. The probability that customer i makes a purchase at t among the products offered by the firm is denoted by the following function:

$$\lambda_i(t) = \lambda_{0i}(t)\psi_i(X_i), \tag{6.1}$$

where,

$\lambda_{0i}(\cdot)$ denotes the baseline hazard function, and
$\psi_i(\cdot)$ is a function of the covariates influencing the timing decision.

The purchase probability of product j by customer i at time t, is, P_{ijt} is given by:

$$\begin{aligned} P_{ijt} &= \frac{e^{u_{ijt}}}{\sum_{j=1}^{J} e^{u_{ijt}}} \\ &= \left\{ \frac{\text{(utility for a given product)}}{\text{(sum of the utilities for all the products)}} \right\} \end{aligned} \tag{6.2}$$

where, u_{ijt} is the utility for product j of customer i at time t.

Then, the joint instantaneous probability of customer i buying product j at time t, $h_i(j|t)$ is given by:

$$h_i(j|t) = \lambda_i(t)P_{ij}(t). \tag{6.3}$$

It is important to note that in the above formulation (Equation (6.3)), the two events purchase timing and product purchase are estimated independently and then multiplied to get the desired outcome. The problem associated with estimating these two terms independently is that the errors associated with each term get multiplied causing a larger error in the final outcome. Further, biases can occur in the parameter estimates of the choice model due to omitting information from the purchase timing model and *vice versa*.

To counter this sampling error problem, a recently conducted research extended the dynamic McFadden model to develop a likelihood function that accurately computes the purchase and timing probabilities for a customer population when buying two or more products (Kumar et al., 2006). The joint likelihood function[1] for customer i, is given by,

$$L_i = \prod_{k=1}^{r_i} \left\{ \prod_{j=1}^{J} \{f_i(t_k, j_k)^{d_{ijk}}\}^{c_{i,k}} \right\} s_i(t_k)^{(1-c_{i,k})}, \tag{6.4}$$

where,

r_i is the number of purchase occasions (spells) for customer i,

$c_{i,k} = \begin{cases} 1, & \text{if the } k\text{th spell for customer } i \text{ ends in a purchase,} \\ 0, & \text{otherwise.} \end{cases}$

$d_{i,j,k} = \begin{cases} 1, & \text{if customer } i \text{ chooses product category } j \text{ in spell } k, \\ 0, & \text{otherwise.} \end{cases}$

$f_i(t_k, j_k)$ represents the joint probability of purchase product category j in time period t, and $s(\cdot)$ denote the survivor functions of the log-logistic distribution in purchase timing model.

Using a software (e.g., MATLAB or Gauss) the purchase behavior of the sample customers and other customer data were processed through the likelihood function (Equation (6.4)) to derive the purchases of different products at different times by different customers in the sample. To test the accuracy of the model, the study considered a multinational B2B company catering high-tech products and services to *Fortune* 500

[1] For a detailed explanation of the McFadden model, refer "Social Science Duration Analysis" by James Heckman and Burton Singer (1985), in *Longitudinal Analysis of Labor Market Data*. Cambridge University Press.

clients. For the study, three years of data (2000–2002) for a sample of 20,000 customers were considered. Using the factors related to purchase behavior and timing, the coefficients for the customer variables were determined, which was then used to derive a probability cube (for all the customers in the database) covering the four quarters that started in January 2003. Using the same set of customer variables, a second probability cube was derived using the traditional approach. The comparison of probabilities of purchase for a single customer over time and across product categories using the traditional and the new method is provided in Table 6.4.

On comparing the probability cubes of the two methods for the B2B company, the new model was found to be better than the traditional method at predicting the customer purchase behavior. For instance, when the new method predicted that a customer had a high probability of purchasing product 1 in a given quarter, it was correct in 85% of the cases. For a similar setting, the traditional method was correct in only 55% of the cases. Table 6.5 gives a snapshot of how the traditional model fared against the new model.

In effect, the new model improved the B2B company's ability to accurately predict customer behavior by about 54%. While the traditional method accurately predicts which products the customer will buy, it performs poorly in predicting the purchase time.

Table 6.4 Comparison of probabilities.

	New model				Traditional model			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Product 1	0.75	0.10	0.17	0.36	0.50	0.70	0.05	0.20
Product 2	0.10	0.15	0.66	0.35	0.40	0.10	0.25	0.60
Products 1 & 2	0.10	0.70	0.10	0.20	0.05	0.15	0.65	0.20

Table 6.5 Comparison of accuracy.

	New model		Traditional model	
	Made a purchase (%)	Did not make a purchase (%)	Made a purchase (%)	Did not make a purchase (%)
Of the customers predicted to buy	85	15	55	45
Of the customers predicted not to buy	13	87	41	59

The new model was tested on a B2C financial services firm as well. For this company, four years of data on 10,000 customers were used to predict the probabilities over the fifth year. The results obtained were strikingly similar to the B2B case. The new model predicted actual purchases accurately 71%–89% of the time, as against to 58%–65% by the traditional model. For this case, the new model improved the company's ability to correctly predict the customer behavior by about 33%.

The results obtained from the two cases have important implications on marketing communications. Based on the cases discussed above, it was inferred that purchase improvement was linked to marketing communication in a highly nonlinear fashion. That is, too much or too little communication can harm a company. Therefore, optimizing the level of marketing communication would not only lower costs for a company, but also increase revenues per customer. The research study also tested this aspect through a field study to see the impact of the new model on the marketing communications strategy.

Accordingly, the customer samples of the B2B and B2C firms were split into a test group and a control group. The communication strategy for the customers in the test groups was determined by the variable relationships and the probability predictions generated by the new model. The contact strategy for the control group was decided by the company's traditional approach. This was combined with information such as revenue per customer, cost of sales and communication, number of contact before a purchase, profit, and ROI that was collected for a year.

When the results were compared, the new methodology improved the B2B firm's profits by an average of $1,600 per customer, representing an increase in ROI of 160%. The improvement when computed for the sample of 20,000 customers resulted in an increase in profits to about $32 million for the sample group alone. When this was extended to their entire customer base of 200,000, the potential profit improvement would total $320 million. Likewise, for the B2C financial services firm, the average profitability improvement per customer was about $400, representing an ROI improvement of 200%. For their sample of 10,000 customers, the increase amounted to $4 million and for their entire customer base the profit improvement would amount to $200 million. It is important to note that, while the new model does save money spent on unreceptive customers, it also does something more valuable — recovering sales that their traditional strategies may currently be losing.

While the model used in this study is a joint model with homogenous parameters, an extension to this model is available (Kumar et al., 2008) In the extension, a joint model with heterogeneous parameters is proposed. This more advanced model is not only accurate in predicting who is likely to buy and when, but also results in higher ROI and profitability. Finally, the relational measures such as customer satisfaction, willingness to repurchase and willingness to recommend are higher for customers who were targeted at the right time with the right offering.

Therefore, by understanding the purchase sequence firms can target the right product to the right customer at the right time. It helps in increasing cross-buy ratio and revenue apart from decreasing marketing costs, thus leading to an incremental ROI. This also helps firms to devise effective cross-sell and up-sell strategies. When integrated with the CLV measure, it can help companies design the most optimal marketing strategy directed toward offering the right product to the right customer at the right time through the most cost-effective channel.

6.5 Targeting Multi-Channel Shoppers

The multi-channel shopping strategy analyses the changing dynamics of sales and customer communications in the present market. With the onset of complex distribution systems within industries and on the Internet, firms are beginning to stretch themselves across several different channels so as to appeal to many different customer segments. These distribution channels are important for growing companies that want to continually maximize overall performance. Constantly reviewing the number of available channels and keeping track of the customers within these channels provides firms the opportunity to innovate, accelerate, grow, change, acquire new customers, adopt new technologies, and reevaluate distribution channel performance. Many customers also expect their favorite retailers to offer a satisfying cross-channel shopping experience, whether it is to browse printed catalogs before buying from e-catalogs, order goods online followed by in-store pickup or do some research online before making store purchases. The drivers of multi-channel shopping and behavioral characteristics of multi-channel shoppers are explained in Figure 6.4 (Kumar and Venkatesan, 2005).

The drivers of multi-channel shopping are classified as customer characteristics, supplier- specific factors and, customer demographics. Customer characteristics include factors like cross-buying, number and frequency of returns, frequency of web-based contacts, tenure of the customer with the firm, and the frequency of customer purchases. In other words, the higher the frequency of these factors, the higher is the likelihood of multi-channel shopping. The supplier specific factors include the various channels used for contact, type of contact channel, and the channel mix. Here again, the higher the degree of supplier-specific factors, the higher is the likelihood of multi-channel shopping. The customer demographics refer to the number of employ-

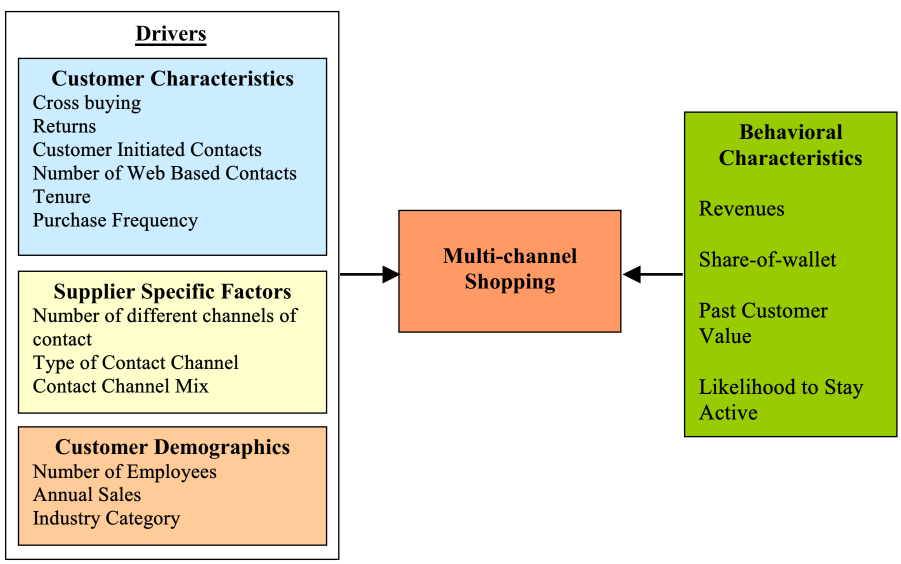

Fig. 6.4 Drivers of multi-channel shopping and behavioral characteristics of multi-channel shoppers.

ees in the firm who serve customers, the annual sales of the firm and the industry category. The behavioral/transactional characteristics refer to the customer-based metrics, which includes revenues, PCV, SOW and likelihood to stay active.

Several firms, including IBM, Merrill Lynch and Citibank, have recognized the benefits of providing products across multiple channels to manage customers in a more efficient manner. In addition, Wells Fargo now allows small businesses to use single online accounts to manage both their business and personal accounts. According to studies, multi-channel shoppers are more loyal and more profitable than single channel shoppers, possibly because they are aware of the options available to them and purchase products in the channel most convenient to them (Neslin et al., 2006). Further, owing to the high opportunity cost of time to switch to other vendors and the familiarity of shopping with the current vendor, makes multi-channel shoppers more loyal and potentially more profitable.

In a recent study, where the mean of customer metrics was compared, it was seen that the mean for customers who shopped in four channels is higher than the mean of customers who shop in a single channel. The results of the study are depicted in Table 6.6.

The results from the study clearly show that the revenue of the firm increased exponentially when the customer shopped in multiple channels as compared to shopping in a single channel. Also, the mean of other metrics like SOW, PCV, the probability of the customer staying active with the firm and CLV increased when the number of channels shopped in increased.

Table 6.6 Comparison of means of customer-based metrics.

	Shopped in single channel	Shopped in two channels	Shopped in three channels	Shopped in four channels
Revenues	$4,262	$5,376	$13,250	$60,076
Share-of-wallet	20%	35%	48%	72%
Past Customer Value	$6,671	$10,874	$22,472	$94,456
Likelihood of Staying Active	0.11	0.15	0.38	0.67
CLV	$3,197	$4,032	$9,938	$45,057

Therefore, we see that maintaining multiple channels of transaction with a customer are considered essential for sustained growth in the current scenario. The three critical aspects of the customer firm relationship in a multi-channel strategy are:

- *Encouraging multi-channel shopping*: Many firms employ various strategies that are designed to encourage customers to shop in multiple channels. To a large extent, the firm's attempt to encourage customers to shop in multiple channels is based on the belief that multi-channel customers have a higher annual purchase volume than single-channel customers.
- *Predicting adoption of channels*: Predicting the time a customer takes to adopt an additional channel would help multi-channel firms in various resource allocations. If multi-channel shopping leads to higher profits, given that marketing communications have a positive effect on customer channel choice, predicting customer channel adoption duration would help mangers further refine their resource allocation decisions by prioritizing channel adoption.
- *Generalizing interaction*: Firms attempt to develop basis for identification of customer–firm interaction factors so that proposed strategies are sufficiently generalized across the firm.

For a firm, several behavioral and psychological aspects determine the rate of relationship development and channel adoption, which have an impact on customer management. In a recent study of several interaction characteristics (ways of communication from firm to customer) and their effect on channel adoption was conducted and their results were analyzed. Figure 6.5 summarizes the interaction characteristics and their effect on customer channel adoption.

As seen from the above figure, interaction characteristics, channel-related attributes, purchase-related attributes, frequency-related attributes, and customer heterogeneity are all drivers of channel adoption. These factors make the customer accept new channels and

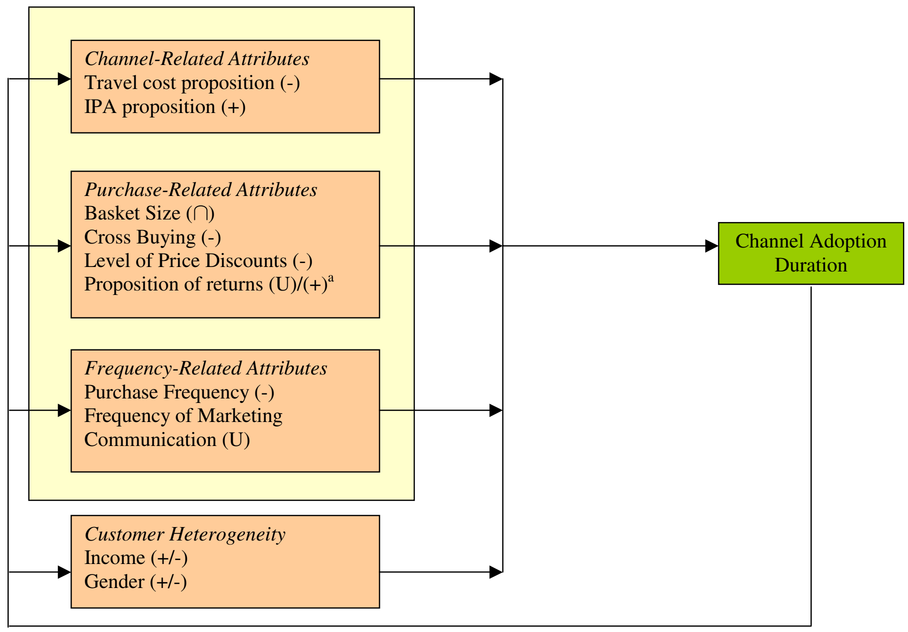

Fig. 6.5 Interaction characteristics for channel adoption duration.

thereby shop across different channels. The different interaction characteristics are:

(1) Channel Related Attributes:

- *Travel Cost Proportion*: It is defined as the sum of distances to the closest stores in each transaction channel (when shopping in two channels) to the sum of distances to the closest store in all available channels. The negative sign in the figure suggests the effect of travel cost proportion on channel adoption duration. The sign indicates that higher the travel cost proportion in the current channel, the shorter is the channel adoption duration.
- *IPA Proportion*: Immediate Product Availability (IPA) is provided by a channel if a customer is able to consume the product immediately after purchase.

With respect to the Internet, this can be thought of as digital attributes (all product attributes that can be communicated through the Internet) that can be consumed or sampled immediately. For instance, when purchasing CDs online, consumers can listen to samples of music before purchasing (Lal and Sarvary, 1999). Channels that do not have IPA cannot provide customers with a rich interaction/experience with the product. The positive sign in the figure suggests the higher the IPA proportions in the customer's current channels, the longer is the channel adoption.

(2) Purchase Related Attributes:

- *Basket Size*: It is the total quantity of items a customer purchases in a single shopping trip. It can also be inferred as higher the basket size (i.e., higher the items purchased in one transaction), the higher the utility provided by the driver. The $\cap$ sign in the figure suggests that channel adoption duration is shorter for customers with either very small or very large basket sizes than for customers with intermediate basket sizes.
- *Cross-Buying*: It is defined as the number of product categories a customer purchases from in a single shopping trip. The negative sign in the figure suggests that higher the level of cross-buying, the shorter is the channel adoption duration.
- *Level of Price Discounts*: Customers perceive a gain when the get discounts as they have paid less for the product, which was originally priced higher. The availability of a discount can lead to channel adoption because of the potential savings the discount provides to the customer. The negative sign in the figure suggests that higher the level of price discounts a customer get, the shorter is the channel adoption.

- *Proportion of Returns*: It is defined as the ratio of the number of returns to the number of products a customer purchases. Product return represents an example in which the customer expresses their dissatisfaction with the product or the services and expects a bargain to remove that dissatisfaction. The U sign in the figure suggests that channel adoption duration is higher for customers with intermediate proportions of return as compared to high or low level of proportion of returns.

(3) Frequency Related Attributes:

- *Purchase Frequency*: Since it is known that customers who have a higher frequency to purchase develop more familiarity with the products than customers who seldom purchase, more interactions allow customers to form impressions about the firm's product. The negative sign in the figure indicates the higher the purchase frequency, shorter is the duration of channel adoption.
- *Frequency of Marketing Communications*: Firms uses contact strategy in one channel to motivate customers to migrate to from one channel to another. The U sign in the figure suggests that the duration of channel adoption is smaller if the frequency of marketing communications is in the intermediate levels when compared to a higher duration if the frequency of marketing communications is very high or low.

(4) Customer Heterogeneity:

- Demographic factors such as Income and Gender that capture observed customer heterogeneity can be expected to add explanatory power to the model. Further, it is possible for some *unobserved heterogeneity* factors to exist. They will be modeled through the process of statistical estimation.

These drivers help predict the adoption of channels for customers, wherein the more channels a customer adopts, the better is the revenue generated by the firm from that customer is likely to be. Since the duration for adopting a third channel is dependent on the duration it takes to adopt the second channel, multiple hazard models that are used to model customer interpurchase times are unsuitable. As a result, the time taken to adopt a channel assumes that the second-channel adoption duration (t_2) and the third-channel adoption duration (t_3) are independent, given a common unobserved risk factor (w_i) that is specific to each individual i.

Under this framework, the instantaneous probability (also called the customer's "hazard function") that customer i will adopt the jth channel (i.e., the second or third channel) follows the modified proportional hazards form.

$$h(t_{ij}, X^*_{ij}) = \frac{(F[t_{ij}] - F[t_{ij} - \Delta])}{1 - F[t_{ij}]} = h_0(t_{ij}) \times \psi(X^*_{ij}, \beta) * w_i, \quad (6.5)$$

where, Δ is the level of aggregation used in the analysis.

In the study t_{ij} was measured in number of days, so Δ represents a day. For customer i, t_{ij} denotes the observed value of the random time to adopt the jth channel. The corresponding hazard model function is represented by $h(t_{ij}, X^*_{ij})$. The hazard model function can also be explained as the instantaneous probability of adopting the jth channel at time t_{ij} given no adoption until time t_{ij}. The baseline hazard is represented by $h_0(t_{ij})$; X^*_{ij} denotes the antecedents of channel adoption duration; $\psi(X^*_{ij}, \beta)$ represents the influence of the antecedents on the hazard of channel adoption; and w_i is the customer specific frailty or the common risk factor. The observed durations, t_2 and t_3 are independent conditional on w_i.

In this model, the baseline hazard represents the probability distribution characterizing customer's channel adoption durations, and $\psi(X^*_{ij}, \beta)$ shifts the hazard up or down. A Weibull baseline hazard was assumed for the time until the jth channel adoption:

$$h_0(t_{ij}) = \lambda_j \gamma t_{ij}^{\gamma - 1}. \quad (6.6)$$

The formulation for the baseline hazard as two Weibull distributions with a common shape and different scale parameters is similar to the bivariate Burr distribution. The following functional form was used for representing the covariate function:

$$\psi(X_{ij}^{*}, \beta) = e^{\beta_0' X_{i0}} * e^{\beta_2' X_{i2}\varphi_2} * e^{\beta_3' X_{i3}\varphi_3}, \tag{6.7}$$

where,

X_{i0} is a row vector of customer heterogeneity variables that are constant over the j channel adoption events,
X_{ij} is a row vector of interaction factors associated with the customer's transaction history when shopping in 1 channel for $j = 2$; and the customer's transaction history when shopping in two channels versus shopping in one channel for $j = 3$,
$\varphi_j = 1$ if the observation represents the jth channel adoption and 0 otherwise,
β_0 is a row vector of coefficients for customer heterogeneity variables, and
β_j is a row vector of event specific (i.e., adoption specific) coefficients for the interaction factors.

A separate set of coefficients was estimated for the second and third channel coefficients to accommodate for any differences in customer behavior when shopping in a single channel (used to predict second channel adoption duration) and when shopping in two channels (used to predict third channel adoption duration). The interaction characteristics are calculated based on customer's transactions before they adopt a new channel. This allowed for the control of the possibility of endogeneity of the drivers of channel adoption. The likelihood function for model framework is represented as:

$$\begin{aligned} L = \prod_{i=1}^{n} \prod_{j=2}^{3} \big\{ &[\lambda_j \gamma t_{ij}^{\gamma-1} w_i e^{\beta_0' X_{i0} + \beta_2' X_{i2}\varphi_2 + \beta_3' X_{i3}\varphi_3}]^{\delta_{ij}} \\ &\times \exp[-\lambda_j t_{ij}^{\gamma} w_i e^{\beta_0' X_{i0} + \beta_2' X_{i2}\varphi_2 + \beta_3' X_{i3}\varphi_3}] \big\}^{g_{ij}}. \end{aligned} \tag{6.8}$$

A multi-channel experience for customers has the potential to improve two critical aspects of firm: customer retention and customer growth. The primary reasons that suggest customers provide more profits when they shop in multi-channels are:

- Firms can provide several add-on services to customers through multi-channels.
- Customers who shop in multi-channels are exposed to the services the firm provides and therefore are expected to be more satisfied with the firm and thereby develop a deeper relationship with the firm (Venkatesan et al., 2007).

The channel migration campaigns should target customers who provide higher gross profits, purchase across product categories, and transact frequently with the firm. The channel adoption rate increases at a diminishing rate with each additional product return per purchase occasion. Hence, the focus should primarily be on customers who make fewer returns per purchase. A critical factor influencing channel adoption is marketing communication. The above-mentioned factors translate into multi-channel customers potentially allocating a higher SOW to the firm and therefore providing higher profits.

6.6 Maximizing a Customer's Brand Value

A typical dilemma faced by any corporate board is whether to invest in building brands or to invest in building the customer base. Which of the above routes ensure maximum profitability? Strong brands increase loyalty and devotion. Weak brands drive customers to the competition. The answer would be to invest in both. Further, it would be difficult to estimate how investing in brand-building contributes toward attaining higher profitability from the customers. A key to address these issues is to establish a link between brand value and CLV to manage individual customer brand value. This results in maximizing the CLV. The link between Individual Brand Value (IBV) and CLV is established in a series of steps, as illustrated in Figure 6.6 (Kumar and Reinartz, 2006).

The first step, CLV of the customer base is measured. The second step, involves customer selection. Here, the customers are ranked based on their CLV and a sample (10% of each decile) is generated so that a database with high variation in CLV is obtained. The third step, for the

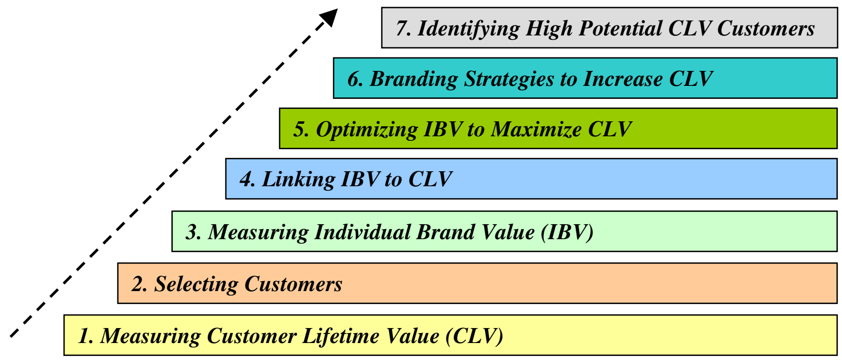

Fig. 6.6 Managing an individual's brand value and customer lifetime value.

set of customers, the measurements for the individual's brand values are obtained. These individual brand values include constructs such as brand awareness, perceived image of the brand, trust for the brand, emotional attachment toward the brand, brand loyalty, and positive word-of-mouth.

In the fourth step, the IBV is linked to the CLV. In other words, the customer's computed lifetime value is expressed as a function of values of individual brand preferences that were obtained in step 3. Then, measurements of individual's brand value are optimized to maximize CLV. After this, the optimized individual brand values are translated to brand management strategies, and the success of brand management strategies are measured at an individual level based on CLV. Finally, the potential customers are targeted by prioritizing and selecting customers based on CLV and by identifying valuable potential customers based on the profiling of existing high CLV customers. The CLV driven by a potential customer's brand value is calculated by estimating brand knowledge, brand attitude, and brand behavior intention of the potential customer.

Brand awareness represents the lowest level of brand knowledge. It can generate a negative brand value if the brand image held by an individual is unpleasant. Brand image reflects a more complex cognitive structure, which is referred as the factual knowledge possessed by a consumer and the way such knowledge is organized.

A study was done to calculate individual's brand value, and its effect on the calculation of CLV (Oliver, 1999). Brand attitude examined in this study incorporates two major components: brand trust and brand affect. Brand trust is described as an individual's willingness to trust a brand's ability to satisfy his or her needs. In a situation where an individual cannot objectively evaluate the quality of a product in advance, brand trust plays a vital role in diminishing the uncertainty in a purchase. The brand knowledge and the brand attitude of an individual establish the groundwork of his or her brand value, brand behavior intentions truly reflects how an individual values a brand by exhibiting purchase intention. An individual may develop brand loyalty if repeat purchases have been observed. Brand loyalty is defined as "a deeply held commitment to repurchase a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand-set purchases, despite situational influences and marketing efforts having the potential to cause switching behavior."

Brand advocacy is defined as a consumer's behavior of joining in a brand community and inviting outsiders to join the community. It is observed that brand communities engage in important activities such as sharing information, perpetuating the subculture, and providing assistance. Consumers differ in their willingness to pay for the product and their taste for quality, such heterogeneity explains variation in consumers' motivations to pay for premium price. However, a firm should not always expect its long-term customers to pay for premium price. A long-term customer may learn alternative product information through time and also expect to be rewarded for his loyalty.

A conceptual framework is suggested as in Figure 6.7, which shows the dynamic process of transferring an individual's brand knowledge to his or her brand attitude, brand behavior intention, brand behavior, and ultimately to his or her lifetime value to a firm. Therefore, this study proposed that an individual's brand value be defined as "the differential effect of an individual's brand knowledge, brand attitude, brand behavior intention, and brand behavior on his or her response to the marketing of a brand."

As customer equity (CE) is the summation of CLV, customer-based brand equity is the summation of individual brand value. This study

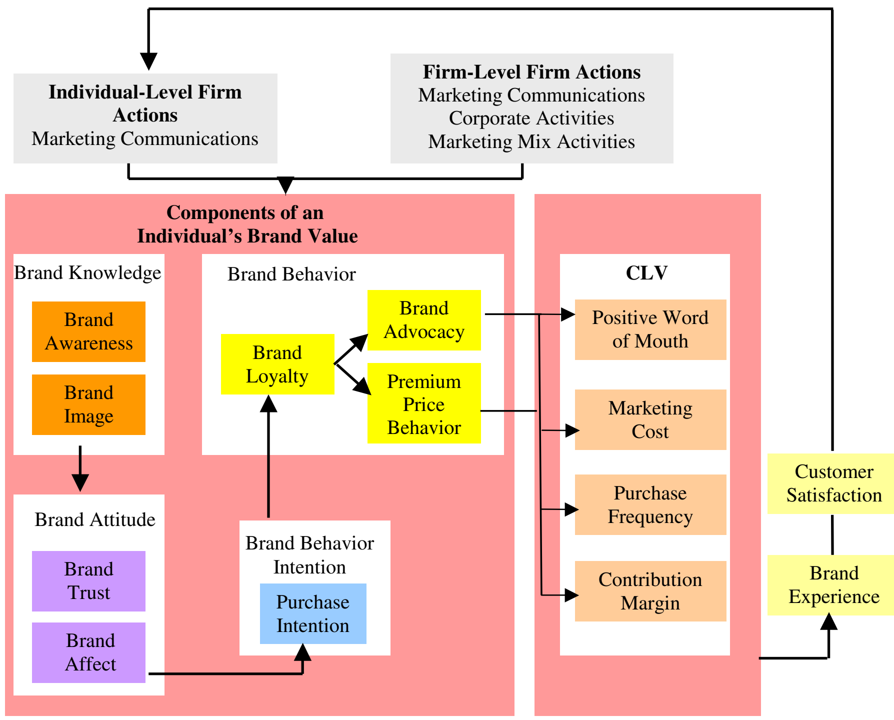

Fig. 6.7 Linking an individual's brand value to the customer lifetime value.

proposed that individual brand value be linked to CLV through brand behavior transferred from brand knowledge, attitude, and purchase intention. Customer equity is the aggregated result of CLV. The financial value of a brand is then generated through the CE. Because of the power of customer base, firms cannot only directly obtain profits from existing customers, but also gain advantages in terms of better distribution from retailers and incremental cash flow from shareholders. In the study, a customer's observed brand value was calculated on a range of 0–1 and his/her attachment to the brand was determined. Figure 6.8 shows scores of different variables that are used to calculate the brand value for Customer A.

Customer A's CLV was calculated to be around \$12,000 and was dependent on eight variables as shown in Figure 6.8. Knowing the values of variables, the measurements of Customer A's brand value to

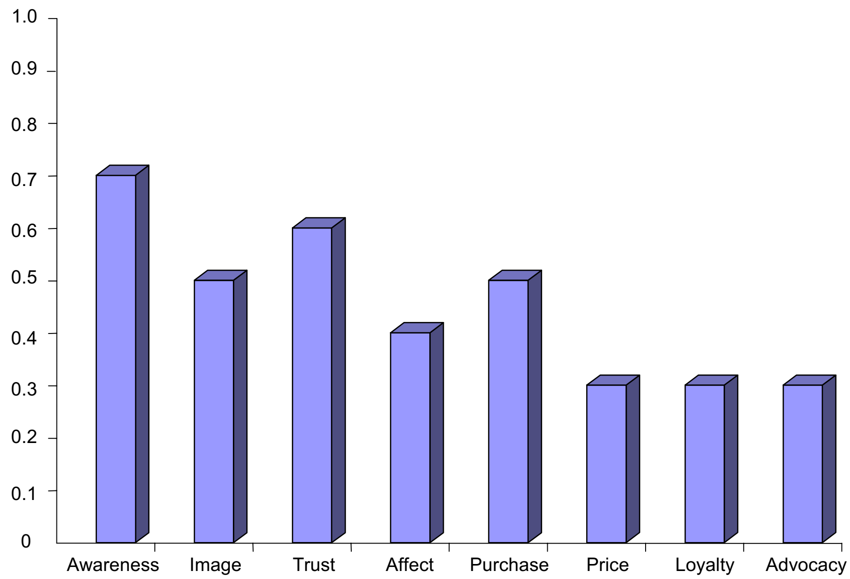

Fig. 6.8 Customer A's observed brand value.

maximize his or her CLV was optimized. After optimization, the brand value of Customer A for each variable increased as is shown in Figure 6.9. It was observed that the value of CLV increased from $12,000 to $18,000 after optimization. Thus, firms can optimize the value of components of Customer A's brand value to maximize his or her CLV. The optimization was subject to budget constraints of marketing resources allocated to customers.

This study has several implications for increasing overall profitability. Certain managerial implications of this study are:

- *Monitor the Overall Performance of Integrated Brand Value*: This model can monitor the overall performance of IBV. Firms can sample a group of existing and potential customers. Then, they can measure their individual brand values. Finally, they can identify the weak components in the individual brand values and come up with different strategies. For example, if in general a customer's brand awareness and brand image are low, firms can encourage new product trials

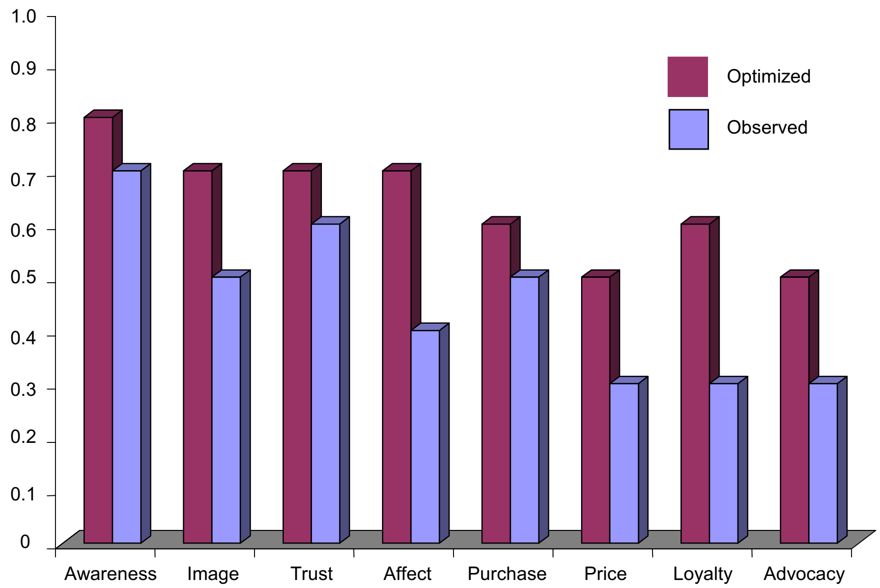

Fig. 6.9 Optimized and observed brand value.

to boost brand awareness. Similarly, if the rating for brand image is not ideal, firms can boost brand image through advertising. It is also interesting to know how much variance in brand attitude is explained by brand awareness and brand image. If brand image plays a bigger role in developing positive brand attitude, firms should come up with strategies to increase the rating in brand image.

Furthermore, it is necessary to understand how purchase intention is driven by brand affect and brand trust. If more importance is placed in brand trust, the advertising message should be objective and contain detailed information about the product to increase customers' trust. If most of the customers sample exhibit high purchase intention but low customer loyalty, firms need to understand the reason behind this. Perhaps, firms can use loyalty programs and appropriate adverting strategies to build positive brand knowledge and attitude that leads to behavior loyalty.

Finally, brand advocacy and premium price behavior are the most important aspects of individual brand value. This is because, customers not only commit to the brand through frequent purchase but also go one step ahead to advocate the brand and pay a higher price.

- *Managing Brand at the Individual Level*: Since "True friends" (see Figure 6.1) are the most valuable asset of a company, firms can manage brand at the individual level to make sure that the brand message appeals to this segment of customers. Firms should select a sample of true friends and constantly monitor their individual knowledge structure, positive brand attitude, purchase intention, and brand behavior. Once the individual decision process is understood, personalized marketing action can be performed to send the right message at the right time so that the individual's CLV and IBV can be simultaneously maximized. However, since brand value has been managed at the aggregate level for so long, too much confusion will ensue if managing brand at the individual level is suggested at this time. Therefore, for the purpose of this proposal, we only suggest managing brand at the segment level.
- *Managing Brand at Segment Level*: In order to appropriately segment the market according to their CLV and IBV values, firms can select a sample of customers with a range of variety in profiles. Their CLV values and IBV are then estimated. As shown in Figure 6.10, customers with high CLV values and high IBV can be referred to as "TRUE LOYALISTS." The marketing strategy is to keep building positive brand knowledge and attitude with this segment of customers. Customers with low CLV values and high IBV are called "POOR PATRONS." The brand investment for this segment of customers should be moderate. Firms can encourage cross-buy and add-on selling to increase the customers' CLV values. Customers with high CLV values and low IBV are called "ACQUAINTANCES." Firms should think of other ways to increase their CLV with limited brand

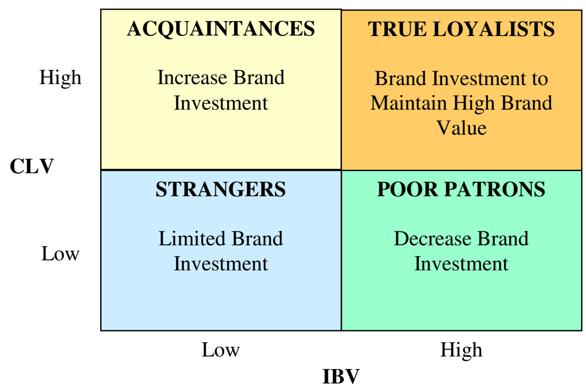

Fig. 6.10 Segmented strategies to manage CLV and IBV.

investment. Customers with low CLV values and low IBV are called "STRANGERS." Firms should invest moderately on the strangers who have the potential to increase their CLV values. Finally, the rest of the customers can be segmented by matching profiles with those of the selected sample of customers (Kumar et al., 2008).

6.7 Preventing Customer Churn

The cost of retaining an existing customer is usually far less than the cost of acquiring a new customer. While trying to prevent customer churn, it should be noted that different customers behave in a different fashion. Firms should design the marketing plan accordingly. Scientific models (such as Dynamic Churn models) are used to predict future customer behavior and help firms decide which customer/distributor is likely to quit and at what time. These models empower the managers to execute timely, customer-specific marketing interventions that result in an increase in ROI. Some of the strategic questions faced by managers in implementing this strategy are (Kumar and George, 2008):

- Should we intervene?
- Which customers should we intervene with?
- When do we intervene?

- Through which channel do we intervene?
- What do we offer them?

The solution to these questions lies in building propensity-to-quit models and integrating them with the CLV based models. To decide on the intervention necessity, it is essential on the part of the managers to study customer quitting tendencies. For instance, consider three customers — Customer A, Customer B, and Customer C. The predicted propensities-to-quit over time (July 2004–July 2005) is illustrated in Figure 6.11.

Accordingly, Customer A's intention to quit does not change and is denoted by a straight line. Though customer B does not exhibit a quitting tendency initially, he shows an increase in propensity to quit from January 2005. Customer C, represented by a steep curve, shows a strong tendency to quit early on. Clearly, this indicates that Customers B and C are likely to quit in the near future.

Once the need to intervene and the customers to be retained have been decided, firms have to identify when the intervention has to be made. The answer to this question lies with a proactive intervention strategy. In other words, the customers who show a strong tendency to quit (in this case Customers B and C) have to be intervened to prevent customer attrition. It is to be noted that intervention should

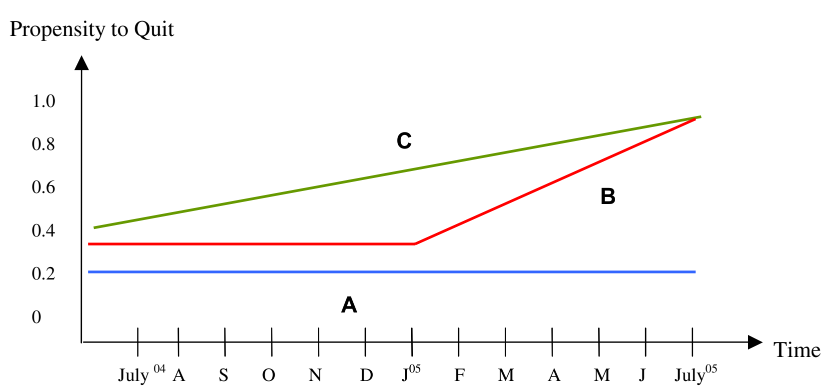

Fig. 6.11 Predicting propensity to quit.

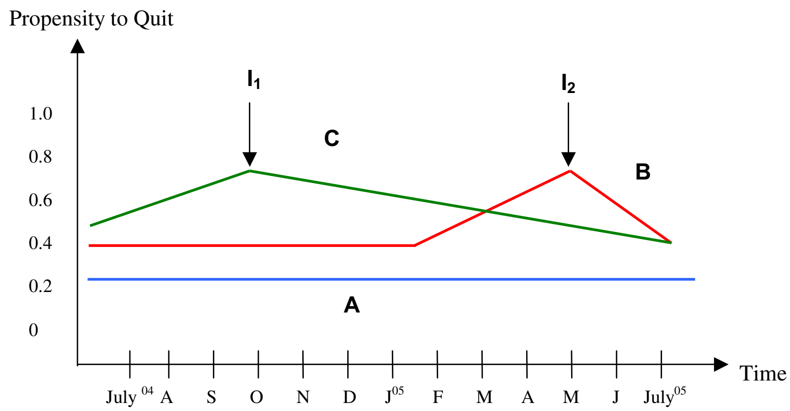

Fig. 6.12 Proactive intervention strategy.

be made only when the customer is profitable. Figure 6.12 shows the time periods in which Customers B and C are intervened.

In the above figure, points I_1 and I_2 denote the intervention points when customers B and C should be retained. This is followed by a decrease in propensity to quit on the part of the customers. Here, Customer B is being retained in April 2005 and Customer C in October 2004. The reason for the time lag between different customer intervention points stems from their respective propensities to quit. While Customer C has to be retained early on, Customer B can be retained at a later stage. The companies can then decide the channel of intervention and the offer through which the intervention is to be made, based on individual customer characteristics and each customer's CLV. Thus, proactive intervention strategies help companies to pre-empt customer attrition and thereby increase ROI.

Customer attrition impacts a firm in several ways. One direct impact is the loss of revenue from the customers who have defected. The extent of revenue loss depends on the level of service commitments the customer had with the service provider. The higher the expected revenue from the customer, the more is the impact on the firm. Closely related to this expected revenue loss is the lost opportunity for the firm to recover the acquisition cost incurred on the customer. It is a usual practice in many service industries to offer incentives to new customers. Because of competitive pressures, the cost of the incentives offered coupled with other acquisition costs are so high that it (in some cases) takes several months to break even. According to J.D. Power and Associates, customers who are satisfied with their carrier's service are more likely to remain loyal and spend more money on additional services.[2] Further, the firm also loses opportunity to up-sell/cross-sell to the customers who have defected — this can be treated as a loss of potential revenue.

Hence, it is extremely important for the firms to develop a successful proactive strategy to prevent attrition. However, the biggest challenge for firms in this case would be to find out how firms identify the customers who are likely to defect. The effectiveness of the intervention strategy depends on the accuracy of the selection of customers. If the customers selected do not match very well with those who are actually going to defect in the future, the firm will be incurring resources on customers who will not defect and will fail to target customers who will actually defect. The other important questions that are of importance are:

(1) When are these customers likely to defect? Can the firm predict the time of churn for each customer?
(2) Should the firm intervene in all the cases?
(3) When should the firm intervene?
(4) How much should the firm spend to avoid attrition of a particular customer?

Answers to these questions will help the firms to develop an effective intervention strategy to prevent attrition and to improve the firm performance.

A study was conducted on a telecommunication firm to identify the answers to the above problems. The firm was facing the challenge of retaining its customers and wanted to intervene to prevent the attrition of its profitable customers. Before it implemented an organization-wide intervention strategy, the firm wanted to analyze the impact of and intervention strategy through a field experiment.

[2] http://www.jdpower.com/corporate/news/releases/pressrelease.aspx?ID=2007118

To understand the impact of an intervention strategy, it was critical to compare the revenue outcome from a group of customers who are targeted with an intervention strategy (test group) with that of a similar group of customers who were not intervened (control group). The customers in both test and control groups should be similar in terms of their propensity to quit and their worth to the company measured in terms of their individual customer lifetime values in addition to other exchange and customer-specific characteristics. Hence, the first step in selecting two groups of customers for the field experiment is to compute the propensity to quit for all customers in a large sample selected from the customer database. The firm selected a particular cohort of customers and computed their individual propensities to quit using the accelerated failure hazard model. The firm also computed the CLV of each of these customers. Since the firm was interested in retaining its high value customers, those with negative or very low CLV values were not included either in the test or control group.

The firm then selected two groups of customers based on matched-pair comparisons. In addition to having very similar CLVs and propensities to quit, the customers in the two groups had similar characteristics such as frequency of purchase, usage rate, types of services subscribed, and different demographic variables such as household income and occupation. The customers belonging to the test group were targeted with an intervention offer while those in the control group were not offered any additional benefits. The study was carried out for 1 year. The performance of the two groups in terms of number of customers who defected, the revenue loss and the net profit was compared at the end the study period to understand/determine the impact of the intervention strategy. Figure 6.13 shows the design of the study. The empirical results are shown in Table 6.7.

The Hazard function for the model was given as

$$\lambda(t_i) = \frac{\gamma_{0i}\gamma_{1i}^{\gamma_{0i}} t_i^{\gamma_{0i}-1}}{1+\gamma_{1i}^{\gamma_{0i}} t_i^{\gamma_{0i}}}, \tag{6.9}$$

where, the two parameters of the log-logistic model are γ_{0^i} and γ_{1i}, both of which are greater than zero.

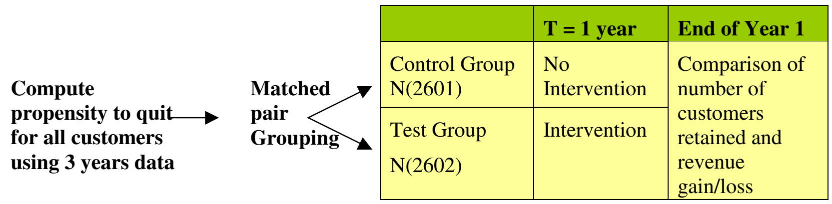

Fig. 6.13 Study design.

Table 6.7 Effect of customer churn.

	No intervention	Intervention
Number of customers sampled at the beginning of the study	2,601	2,602
Time period of study	1 Year	1 Year
Number of customers at the end of the study	1,768	2,412
Numbers of customers lost	833	190
Number of customers saved	—	643
Revenue gain	—	$385,800
Revenue cost	—	$40,000
Incremental profit	—	$345,800

Customers are chosen for marketing communications based on their responsiveness to previous marketing communications, and the strength of their overall relationship with the firm. Therefore, the log of the level of marketing communications was modeled as follows:

$$\log(m_i) = \gamma_0 + \gamma_1 * \beta_{0i} + \gamma_2 * \beta_{1i} + \varepsilon_i, \tag{6.10}$$

where,

$\gamma = \{\gamma_0, \gamma_1, \gamma_2\} =$ a $3 * 1$ coefficient vector,
β_{0i} is the intercept term,
β_{1i} is the response coefficient for marketing communications,
ε_i is the error term which is distributed, Normal $(0, \sigma_m)$.

The likelihood function for our model framework is provided by

$$L = \prod_{i=1}^{n} \{[\lambda(t_i)]^{c_i} s(t_i) p(m_i)\}, \tag{6.11}$$

where,

$\lambda(t_i)$ is the hazard function of lifetime duration for customer i,
$s(t_i)$ is the survival function of lifetime duration for customer i based on the hazard function,
c_i is the indicator function for right censoring, is equal to 1, if the customer terminates the relationship before the end of the observation time frame,
$p(m_i)$ is the function used to model the marketing communications. The log of marketing communications is used in Equation (6.10).

The results indicated that firms can realize higher profits by retaining more customers. The study was carried out on a sample of 2,601 customers for a period of 1 year. They were categorized in two groups — "No Intervention" and "Intervention." The number of customers lost in the No Intervention group was 833 as only 1,768 customers remained by the end of study. In the Intervention group 2,412 customers stayed on till the end — only 190 customers were lost. Owing to a lesser churn of customers in the Intervention group the firm gained revenue of $385,800 as compared to a retention cost of $40,000, making an overall profit of $345,800.

6.8 Targeting Profitable Prospects

Targeting profitable prospects is an important planning phase for firms. Accurate customer profiling analysis helps firms implement a solid marketing strategy. Firms target prospects precisely by choosing segments that match the firm's customer base and channels that match the customer's preferences. Firms should apply the knowledge gained about the new customers across the entire organization, cultivating customers, synchronizing departments and approaching customers on the one-to-one basis and providing solutions to their needs and wants.

Reaching out to potential customers with targeted offers has never been easier. Discovering the firm's best target requires extensive customer profiling research. Firms need comprehensive, reliable customer profile information to effectively customize their marketing plans. Targeting specific audience and understanding the demographic characteristics, lifestyle behaviors and purchase preferences that drive customers' buying decisions leads to a successful marketing campaign.

Closing the Customer Contact Loop: Firms collect the information they need by adding market data to the firm's existing database with customer profiling. This helps the company to improve the profitability of their current customer base and find additional profitable customers. This will enable them to achieve a closed-loop relationship that capitalizes on every customer contact. By incorporating the customer profiling lifestyle and market information they need, they can implement more effective, customized cross-selling and retention strategies. This approach also allows them to adapt to changes at each stage in the customer's relationship with a targeted audience, from customer acquisition to customer retention to overall growth.

Reaching the Right Customer with the Right Offer: It is critical for firms to approach the right customer with the right offer. This feature starts with profiling customer activities, which would help firms identify the customers who need to be retained. Further, with knowledge about tastes and preferences of the customers and prospects, the marketing messages flowing from the firm can be customized to deliver the greatest impact on the intended targets. This would ensure a longer and more profitable relationship between the firm and the customers.

A company can effectively manage its customers by implementing the above-mentioned strategies. The following section provides illustrations when the CLV framework was implemented in B2B and B2C settings.

7

Implementing CLV Framework in a B2B and B2C Scenario

Data collection for a relatively large customer group is a very tedious and expensive task. Therefore, the implementation of CLV framework in the B2B and B2C scenario presents a great challenge for organizations. Organizations, which sell through intermediaries, find it impossible to gather data for customers as they are not in direct contact with end customers. For developing customer level strategies, the data needs four essential characteristics. They are:

- Customer-level should be available.
- The data should contain all the transaction information including past customer value, recency, frequency, and contribution margin to derive the drivers of profitability from the data.
- The longer the span of period over which the data is collected the better it is. At the least, firms should collect data over a 2 to 3 year period.
- Marketing touch information should be included in the data. The data should comprise of all the marketing touch methods used (e.g., mails, emails, etc.) and the date on which each touch occurred.

After collecting data with these characteristics, the firm can develop a customer-level strategy to aid managers in making decisions.

7.1 CLV Framework Applied to a B2B Firm

Data collection is relatively easier for B2B firms because of their direct contact with the end users. The implementation of marketing strategies within B2B firms was analyzed and the best practices for anticipating common challenges in the process were suggested. The practice involved several steps for successful implementation.

- The firm rank-ordered its existing customers to decide which customers to target and which ones to ignore. The ranking was done using the CLV method.
- The next step was to identify the high valued customers by understanding their specific characteristics and developing a unique marketing effort to capture them. This also helped the firm in identifying future customers.
- The firm decided on its optimal contact strategy to these customers, in terms of type and frequency of communication.
- The final step included using the purchase timing and timing model, which helps firms to isolate different time periods when these customers were most likely to purchase these products or services.

One of the main reasons for the failure of marketing strategies is that, either the firms do not support the effort fully or the implementation was not properly customized and executed across each department. However, such obstacles can be overcome by motivating employees, tracking the performance of marketing strategies, and constantly checking if the implementation is progressing as planned. Thus, revolutionizing the way employees approach customers and adapting firm-level strategies that drive the thinking of the company and its employees hold the key in the implementation of successful CRM strategies.

7.2 CLV Framework Applied to B2C Firm

In some cases, with the collection and analysis of transactions of individual customers being increasingly available in the loyalty card retailer databases, customer data intermediaries (CDIs) such as Catalina Marketing are enabling B2C firms to offer targeted coupons to customers. Strategies for such CDIs include whether to offer the targeting service exclusively, the level of customer information to include and the price charged to B2C firms (Pancras and Sudhir, 2007).

In many cases, the company may have the sales related date for their intermediaries but may not have transaction data for all the end consumers. Further, the contribution from each customer may be low. Hence, managing business at an individual level may not be the right strategy. This is because of the high cost associated with communicating to a customer as compared to the contribution from an individual customer. Instead, the firm will be interested in knowing the drivers of consumption for different consumer age groups so that customer value from that age group can be maximized (Kumar and George, 2007).

Consider a soft drink manufacturer who usually sells through the intermediary channels. This calls for gathering information on consumption and demographic variables from a large number of respondents from different age groups. For instance, customers can first be grouped into six age groups. The age groups can be <13 years, 13–18 years, 18–29 years, 30–39 years, 40–50 years, and >50 years. Then, a sample of customers can be randomly selected within each group for all the age groups. Following this, information about the quantity of soft drinks (specific brand) consumed by each respondent and the demographic variables can be collected using a questionnaire survey. In the case of the <13 years age group, information can be collected by contacting the head of the household. Based on this, the firm can arrive at a rough estimate of the lifetime value of a customer in each age group. It is expected that the consumption pattern in one age segment may be quite different from that in another.

When the firm estimates the average yearly consumption of a specific brand of soft drink for different age groups, it can calculate the total consumption by an average consumer in his or her lifetime.

However, the variation in consumption within an age group may be high. This problem can be overcome by identifying the demographic variables that explain the variation in consumption pattern of customers within an age group either by regressing the average monthly consumption quantity on different demographic variables or by using other suitable statistical techniques. The average monthly consumption quantity (CQ) can thus be expressed as a function of certain demographic variables, as given below:

$$\begin{aligned}\text{CQ}_i = f(&\text{Age, Education, Income, Occupation, Gender,}\\ &\text{Ethnicity, Religion}, \ldots)\end{aligned}$$

Identifying the drivers of consumption patterns helps the firm to predict the lifetime value of customers in that age group. Firms can then formulate suitable marketing strategies that can maximize the customer value for each age group. It can make use of publicly available data such as the census to collect information on demographic variables of customers in different age groups, as well as the growth in each age segment of the population. This information, along with the drivers of lifetime value, can be used to predict the lifetime value of customers in each group (i.e., total of lifetime values of all the customers in that segment). This will help the firm to direct its marketing efforts to the high-value customer segment. It can also use the profile information of high-value customer groups to target high-potential prospects. Collectively, these two strategies will maximize the customer equity of the firm.

Having looked at the development and implementation of a CLV framework, it is essential to consider the challenges that an organization will face while implementing such a framework. The following section details these challenges.

8

Organizational Challenges in Implementing a CLV-Based Framework

It is clear that firms can benefit by developing a relationship with the customers rather than restrict themselves to a transaction-oriented approach. This benefit can be accrued by acquiring and retaining profitable customers, developing the right communication and marketing strategies, and allocating resources optimally so that the profits are maximized. By classifying customers as high and low value and treating them differentially based on the value they bring to the firm, the implementation of CLV assists firms to manage customers profitably. However, careful treatment of the customer differentiation process is essential to prevent possible consumer backlash (Brady, 2000). This section discusses three key global issues raised by a customer-centric approach — shift from product-centric to customer-centric marketing, challenges in data collection and management, and utilizing the most of a CLV framework.

8.1 Product-Centric to Customer-Centric Marketing

The focus of organizations is changing from product-centric marketing to customer-centric marketing. Product-centric organizations have started to realize that even the customers who are supposedly satisfied are just waiting for a reason to defect and move on. Also, most of the customers complain that new customers get special deals that they no longer get.

The basic philosophy of the product-centric approach is to sell products to whoever is willing to buy them. An organization focuses on universal customers, their needs and problems and trying to provide solution for those requirements, while the basic philosophy of the customer-centric approach is to serve customers.

Changing from the product centric to the customer-centric approach also necessitates changes in the organizational structure. The organizational structure for a product-centric firm comprises of product managers and product sales team managers, whereas the customer-centric firm has customer relationship managers. Firms need to realign their organizational structure to successfully adopt the customer-centric approach. Wells Fargo, a leading financial institute has realigned its organizational structure by creating a two-tiered sales structure wherein a relationship manager manages externally focused relations with the customers and a product manager who is internally focused and provides input for the product development and helps the relationship manager to sell the products more effectively. The difference between a product-centric approach and a customer-centric approach is provided in Table 8.1.

The payoffs of applying a program, which focuses on the customer-centric approach, are:

- Marketing gains for many consecutive years.
- Efficient and timely services.
- Better understanding of customers.

Thus, looking at the current scenario it can be observed that companies are changing their focus from the product-centric to the customer-centric approach so that they can improve profitability (Shah et al., 2006).

If a firm wants to be customer-centric in its approach, there has to be an interaction between the firm and the customer, between customers, and between firms. In the current scenario, the timely and

Table 8.1 Difference between product centric and customer-centric approach.

	Product-centric approach	Customer-centric approach
Basic philosophy.	Sell products to anyone who will buy.	Serve customers. All decisions start with the customer and opportunities for advantage.
Business orientation.	Transaction oriented.	Relationship oriented.
Product positioning.	Highlight product features, and advantages.	Highlight product benefits in terms of meeting individual customer needs.
Organizational structure.	Product profit centers, product managers, product sales team.	Customer segment centers, customer relationship managers, customer segment sales team.
Organizational focus.	Internally focused. New product development, new account development, market share growth, and customer relations are issues for the marketing department.	Externally focused. Customer relationship development, profitability through customer loyalty. Employees are customer advocates.
Performance metrics.	Number of new products, profitability per product, market share by product/sub brands.	Customer share-of-wallet, customer satisfaction, customer lifetime value, customer equity.
Management criteria.	Portfolio of products.	Portfolio of customers.
Selling approach.	How many customers can we sell this product to?	How many products can we sell to this customer?
Customer knowledge.	Customer data are available.	Customer knowledge is a valuable asset.

efficient management of interactions within an organization is recognized as a major source of competitive advantage. This interaction firm and customer, between customers and firms can be defined as "*Interaction Orientation*" (Ramani and Kumar, 2008). Traditionally, firms have been following a product, sales, or a market orientation but today there is a compelling need to evaluate the feasibility of adopting an Interaction Orientation.

Firms have gradually moved from a product-oriented approach to an interaction approach. Initially, firms were product-oriented and the manager's focus was on making superior products. Then, marketing strategy oriented firms (firms where the focus is less on the quality of the product and more on the sales interaction) became popular. Sales-oriented firms believed that aggressive selling and promotional

Table 8.2 Marketing approaches and characteristics.

Firms	Key characteristics
Product-oriented	• The consumer will choose products that offers the best quality, performance, and innovative features. • The product is viewed as a source of business for the firm. • Manage product portfolio; and transaction oriented. • Customer-to-customer linkage is not strategically important. Customer data is considered as a control mechanism.
Sales-oriented	• Sales efficiency and effectiveness is the focus. • The relevance of product or market is of secondary importance. • Pushing the product is more important than creating a value for the product.
Market-oriented	• Marketing activities are conducted for a firm's customer. • The customer is viewed only as a source of business for the firm. • The strategic importance of customer-to-customer linkage is not recognized. • The need of coordination is seen as being limited to the functional departments within a firm.
Interaction-oriented	• Marketing activities are conducted with the customer. • The customer is viewed both as a source of business and as a business resource for the firm. • The strategic importance of customer-to-customer linkages is recognized and included in the customer empowerment component. • The effect of the network economy on the strategic importance of managing and coordinating outsourced production and service is recognized and included in the interaction response component.

campaigns may lead to higher profitability. The concept was practiced more aggressively for products like insurance that customers would not think of buying. The concept of the market-oriented approach started in the mid-1950s. The focus shifted from products to customers and products were designed to suit the needs of the customers. Managers were concerned about finding the right product for their customers.

Finally, the focus has moved to the interaction-oriented approach wherein customers are an integral part of the marketing strategy of the firm. The inputs from customers are treated as a resource for the firm. Table 8.2 represents the different approaches followed by firms and the characteristics of these approaches (Kotler and Keller, 2006).

In a customer-centric approach, the focus is on customers and all organizational activities are centered on them. This approach allows firms to learn about new and latent customer preferences by observing the customer's purchase and behavioral history. Further, the firms can now add genuine value to customers by offering customized products and service propositions. However, changing from a product-centric to a customer-centric strategy may not be always easy. It requires a concentrated effort by the top management to change the organizational-level philosophy of doing business. It may also involve realignment of organizational roles and integration of different functions. Such a transition would lay the foundation for firms to implement CLV-based strategies.

8.2 Challenges in Data Collection and Management

Since the dramatic increase in data storage technology, it is now possible for firms to collect individual-level customer data covering a large number of variables for computing CLV. Some key informational needs are demographic/firmographic information, the value of purchase, products purchased in each occasion and, the number, time, and type of marketing contacts. Despite the decrease in data storage costs over the years, many firms face challenges while identifying the right informational needs, integrating the data, and utilizing the available information. Therefore, before starting to collect the information firms should address these relevant issues in order to manage the data more effectively. Firms face challenges while collecting information about prospects and competitors' customers. This information is important for the process of acquisition. Catalog retailers and the global airline industry, for example, will have to cooperate with competition so that they can obtain this information (Bell et al., 2002).

Advances in customer data collection, storage and targeted promotion delivery have given rise to the use of Customer Data Intermediaries (CDIs) by marketers who can customize the marketing mix for individual customers. CDI is a type of a firm that specializes in collecting customer behavior and demographic data and offers customer-specific marketing services. They are a viable option for marketers to explore for offering effective marketing services (Pancras and Sudhir, 2007). Currently, the demand for CDI services is being fuelled by the widespread adoption of customer relationship management and one-to-one marketing. Some of the popular CDIs are Catalina Marketing, DoubleClick, Experian, VT & NH Direct Marketing Group, Harte-Hanks, and Q-Interactive.

Despite the new advancements in marketing services, marketers do face challenges in data management. The most common pitfall in data management lies in its execution. For instance, a telecommunication company was planning to introduce a new CRM initiative. The initiative included formation of a special unit, which was responsible for providing users the required inputs through the implementation of the CRM initiative. However, the management decided not to communicate the initiative to its internal and external users until it was near completion. The management failed to generate awareness and the desire to participate among the users. By the time the management was ready to train the internal and external users, more than half of the users were not aware of the ongoing initiative and were not keen in undergoing training. As a result, the initiative was delayed beyond the implementation date and incurred a huge loss. Therefore, the CRM initiative should be well communicated to the internal and external users. Even the slightest of discrepancies should be communicated so that errors are eliminated.

8.3 How to Make the Most of the CLV Framework

In order to make most of CLV framework, the top management must support integrating all the corporate functions to focus on customer value. As discussed in the previous sections firms should shift their focus from the product-centric to the customer-centric strategy. Firms should take care in establishing systems and technology that assist in the customer management initiative. The management should understand the current demand of the firm and should identify the path to profitability. The needs of customers should be prioritized while maximizing profitability. They should identify the drivers of CLV and execute a marketing strategy that fits the scenario. Forward-looking metrics like CLV should be adopted along with marketing strategies like customer selection and segmentation for superior decision making.

Firms spend billions of dollars every year on marketing to potential customers and managing relationships with existing ones. A keen understanding of the underlying marketing decisions is essential for companies to target only those customers who may want a particular product or to suggest additional products that current customers may want to buy. Incorporating these decisions with related technologies allow companies to reach customers through many channels, improve overall effectiveness of their marketing communications and thereby increase their potential profits.

8.4 The Future of CLV

Establishing and maintaining effective customer relationships is critical for marketers and firms. This survey discusses CLV as an important metric that marketers need to acquire, grow, and retain the “right” customers. The challenge that most marketing managers face is to achieve convergence between marketing actions and marketing relations.

The CLV framework discussed in this survey relies on customers' personal and behavioral information. While gathering and using customer level information, firms should be aware of the privacy issues and take steps to gain the confidence of customers. The CLV framework is also expected to undergo further sophistication and improvement. Improvements are expected in (1) measuring CLV, (2) a better understanding of the antecedents or drivers of CLV, and (3) emergence of evidence regarding the importance of using CLV as the metric for resource allocation. The concept of resource allocation stems from the broader and critical issues of marketing accountability.

In the current scenario, a firm takes 30 days to 1 year to obtain a 360 degree view of a customer. In the future, the challenge for a firm will be to take marketing action within a day or even the instant a customer walks in. For this to be possible, firms have to be equipped with the necessary systems and controls to capture relevant customer information and produce instantaneous actionable marketing strategies. Therein lies the future of CLV to make the process so fast that a marketing plan is available for every customer as soon as the information is provided.

References

Bell, D., J. Deighton, W. J. Reinartz, R. T. Rust, and G. Swartz (2002), 'Seven barriers to customer equity management'. *Journal of Service Research* **5**(1), 77–85.

Berger, P. D. and N. I. Nasr (1998), 'Customer lifetime value: Marketing models and applications'. *Journal of Interactive Marketing* **12**, 17–30.

Blattberg, R. C., G. Getz, and J. S. Thomas (2001), *Customer Equity: Building and Managing Relationships as Valuable Assets*. Boston: Harvard Business School Press.

Brady, D. (2000), 'Why service stinks'. *Business Week* pp. 118–128.

Brody, R. P. and S. M. Cunningham (1968), 'Personality variables and the consumer decision process'. *Journal of Marketing Research* **5**(1), 50–57.

Brown, G. H. (1952), 'Brand loyalty — Fact or fiction?'. *Advertising Age* **23**, 53–55.

Cunningham, S. M. (1966), 'Brand loyalty — What, where, how much?'. *Harvard Business Review* **34**, 116–128.

Drèze, X. and A. Bonfrer (2001), 'To pester or leave alone: Lifetime value maximization through optimal communication timing'. Working Paper. Wharton-SMU Research Center.

DuWors, Jr., R. E. and G. H. Haines, Jr. (1990), 'Event history analysis measures of brand loyalty'. *Journal of Marketing Research* **27**(2), 485.

Dwyer, F. R. (1997), 'Customer lifetime valuation to support marketing decision making'. *Journal of Direct Marketing* **11**(4), 6–13.

Ehrenberg, A. (1988), *Repeat Buying: Facts Theory and Applications*. Edward Arnold, London: Oxford University Press, New York, second edition.

Fader, P. S., B. G. S. Hardie, and K. L. Lee (2005a), '"Counting Your Customers" the easy way: An alternative to the Pareto/NBD model'. *Marketing Science* **24**(2), 275–284.

Fader, P. S., B. G. S. Hardie, and K. L. Lee (2005b), 'RFM and CLV: Using iso-value curves to customer base analysis'. *Journal of Marketing Research* **42**(4), 415–430.

Farley, J. U. (1964), 'Why does brand loyalty vary over products?'. *Journal of Marketing Research* **1**, 9–14.

Gupta, S. and D. R. Lehmann (2003), 'Customer as assets'. *Journal of Interactive Marketing* **17**(1), 9–24.

Gupta, S. and D. R. Lehmann (2005), *Managing Customers as Investments: The Strategic Value of Customers in the Long Run*. Upper Saddle River, NJ: Wharton School Publishing.

Gupta, S., D. R. Lehmann, and J. A. Stuart (2004), 'Valuing customers'. *Journal of Marketing Research* **41**(1), 7–18.

Kahn, B. E., M. U. Kalwani, and D. G. Morrison (1986), 'Measuring variety-seeking and reinforcement behaviors using panel data'. *Journal of Marketing Research* **23**(2), 89–100.

Kotler, P. and K. Keller (2006), *Marketing Management*. Pearson Prentice Hall, twelfth edition.

Kuehn, A. (1962), 'Consumer brand choice as a learning process'. *Journal of Advertising Research* **2**, 10–17.

Kumar, V. (2008), *Managing Customers for Profits*. Upper Saddle River, NJ: Wharton School Publishing.

Kumar, V. and M. George (2007), 'Measuring and maximizing customer equity: A critical analysis'. *Journal of the Academy of Marketing Science* **35**(2), 157–171.

Kumar, V. and M. George (2008), 'Predicting and managing customer attrition'. Atlanta, GA: Georgia State University.

Kumar, V. and J. A. Petersen (2004), 'Maximizing ROI or profitability: *Is one better than the other*'. *Marketing Research: A Magazine of Management and Applications* **16**(3), 28–34.

Kumar, V. and J. A. Petersen (2005), 'Using a customer-level marketing strategy to enhance firm performance'. *Journal of the Academy of Marketing Science* **33**(4), 505–519.

Kumar, V., J. A. Petersen, and R. P. Leone (2007), 'How valuable is word of mouth?'. *Harvard Business Review* pp. 139–146.

Kumar, V., G. Ramani, and T. Bohling (2004), 'Customer lifetime value approaches and best practices applications'. *Journal of Interactive Marketing* **18**(1), 60–72.

Kumar, V. and W. J. Reinartz (2006), *Customer Relationship Management: A Databased Approach*. New York: John Wiley & Sons, Inc., first edition.

Kumar, V. and D. Shah (2004), 'Building and sustaining profitable customer loyalty in the 21st century'. *Journal of Retailing* **80**, 317–330.

Kumar, V. and R. Venkatesan (2005), 'Who are the multi-channel shoppers and how do they perform?: Correlates of multi-channel shopping behavior'. *Journal of Interactive Marketing* **19**, 44–62.

Kumar, V., R. Venkatesan, and W. Reinartz (2006), 'Knowing what to sell, when, and to whom'. *Harvard Business Review* pp. 131–137.

Kumar, V., R. Venkatesan, and W. Reinartz (2008), 'Performance implications of adopting a customer-focused sales campaign'. *Journal of Marketing*, forthcoming.

Kumar, V., A. M. Luo and V. R. Rao (2008), 'Linking an individual's brand value to the CLV: An integrated framework'. Working Paper, Atlanta, GA: Georgia State University.

Lal, R. and M. Sarvary (1999). 'When and how is the internet likely to decrease price competition?' *Marketing Science* **18**(4), 485–503.

Libai, B., D. Narayandas, and C. Humby (2002), 'Toward an individual customer profitability model: A segment-based approach'. *Journal of Service Research* **5**(1), 69–76.

Lipstein, B. (1959), 'The dynamics of brand loyalty and brand switching'. In: *Proceedings of the Fifth Annual Conference on the Advertising Research Foundation*. New York: Advertising Research Foundation, pp. 101–108.

Massey, W. F., D. B. Montgomery, and D. G. Morrison (1970), *Stochastic Models of Buyer Behavior*. Cambridge: MIT Press.

Neslin et al., S. (2006), 'Challenges and opportunities in multi channel customer management'. *Journal of Service Research* **9**(2), 95–112.

Oliver, R. (1999), 'Whence consumer loyalty?'. *Journal of Marketing* **63**(special issue), 33–44.

Pancras, J. and K. Sudhir (2007), 'Optimal marketing strategies for a customer data intermediary'. *Journal of Marketing Research* **44**(4), 560–578.

Pfeifer, P. E. and R. L. Carraway (2000), 'Modeling customer relationships as Markov chains'. *Journal of Interactive Marketing* **14**(2), 43–55.

Ramani, G. and V. Kumar (2008), 'Interaction orientation and firm performance'. *Journal of Marketing* **72**(1), 27–45.

Reinartz, W. J. and V. Kumar (2000), 'On the profitability of long-life customers in a non-contractual setting: An empirical investigation and implications for marketing'. *Journal of Marketing* **64**(4), 17–35.

Reinartz, W. J. and V. Kumar (2002), 'The mismanagement of customer loyalty'. *Harvard Business Review* **80**(7), 86.

Reinartz, W. J. and V. Kumar (2003), 'The impact of customer relationship characteristics on profitable lifetime duration'. *Journal of Marketing* **67**(1), 77–99.

Rosset, S., E. Neumann, U. Eick, and N. Vatnik (2003), 'Customer lifetime value for decision support'. *Data Mining and Knowledge Discovery* **7**, 321–339.

Rust, R. T., V. Kumar, and R. Venkatesan (2008), 'Will the frog change into a prince'. Working Paper, Atlanta, GA: Georgia State University.

Rust, R. T., K. N. Lemon, and V. A. Zeithaml (2004), 'Return on marketing: Using customer equity to focus marketing strategy'. *Journal of Marketing* **68**(1), 109–127.

Rust, R. T., V. A. Zeithaml, and K. N. Lemon (2000), *Driving Customer Equity How Customer Lifetime Value is Reshaping Corporate Strategy*. New York: Free Press.

Schmittlein, D. C., D. G. Morrison, and R. Colombo (1987), 'Counting your customers: Who are they and what will they do next?'. *Management Science* **33**(1), 1–24.

Schmittlein, D. C. and J. A. Peterson (1994), 'Customer base analysis: An industrial purchase process application'. *Marketing Science* **13**(1), 41–67.

Shah et al., D. (2006), 'The path to customer centricity'. *Journal of Service Research* **9**(2), 113–124.

Thomas, J. S., W. J. Reinartz, and V. Kumar (2004), 'Getting the most out of all your customers'. *Harvard Business Review* **82**(7–8), 116–123.

Venkatesan, R. and V. Kumar (2004), 'A customer lifetime value framework for customer selections and resource allocation strategy'. *Journal of Marketing* **68**(4), 106–125.

Venkatesan, R., V. Kumar, and N. Ravishankar (2007), 'Multi-channel shopping: Causes and consequences'. *Journal of Marketing* **71**(2), 114–132.

Villanueva, J. and D. M. Hanssens (2007), 'Customer equity: Measurement, management and research opportunities'. *Foundation and Trends in Marketing* **1**(1), 1–95.