Applications of CRM in B2B and B2C Scenarios Part II

V. Kumar, W. Reinartz, *Customer Relationship Management*, Springer Texts in Business and Economics, https://doi.org/10.1007/978-3-662-55381-7_17

Overview

The ability to know exactly who is going to buy what product and when, and the resources and communication strategy needed to make it happen, will no doubt be on the top of the wish list for CEOs. This ability will help the firm invest on the most profitable customer's at the most appropriate time, and in the most effective way. This will not only avoid overspending or under spending on customers but also increase the revenue and profit from them. However, many companies continue to spend resources on large number of unprofitable customers. They could either be investing on customers who are easy to acquire but are not necessarily profitable or trying to increase the retention rate of all their customers, thereby leading to wastage of limited resources. Allocating resources optimally on an individual customer was not a feasible process before the introduction of the customer value framework. By utilizing the customer value framework, researchers have now devised models to allow customer-level actions.

In this chapter we describe the model for arriving at the optimal resource allocation. This model will help a manager know the extent to which he should use various contact channels to communicate to a customer. A model to predict the purchase sequence is described next. The model addresses questions like: (1) What is the sequence in which a customer is likely to buy multiple products or product categories? and (2) When is the customer expected to buy each product? The third model addresses issues related to allocating resources between acquisition and retention with the objective of maximizing a customer's long-term profitability. It tries to answer questions like: (1) What should be the total budget for acquisition and retention? (2) How much should be spent on customer acquisition and customer retention? and (3) How should these expenditures be allocated between contact channels?

Customer attrition has become a critical concern for many industries, such as telecommunication, retail banking, and insurance. With increased competition, a customer has many more choices of products and services from a number of firms. Coupled with increased choices for consumers, firms are constantly trying to acquire high-value customers from their competitors. As a result, firms find it difficult to retain customers as they easily move from one firm to the other (that is, defect). This chapter discusses a CLV-based strategy to manage customer churn. By answering some important questions faced by managers in retaining customers, the strategy discussed here is also implemented in a telecommunications firm that has borne impressive results for the company in retaining customers.

While a firm's aggregate-level brand value perception continues to influence its bottom line performance, it does not provide the firm with a clear set of guidelines as to how to structure their marketing and brand investment strategies. To design and execute effective brand management strategies, firms need to understand exactly how each of their actions will affect the customer's individual brand value. In this chapter, we forward a framework that firms can use to effectively link Customer Brand Value (CBV) to the Customer Lifetime Value (CLV) metric. The strategies developed using this link help firms better understand and redesign their brand strategies to suit the needs of the individual customer.

Many firms are using metrics such as Customer Lifetime Value to identify their «best» customers and then allocating resources to target these customers with the highest CLV for referral campaigns. However, such programs tend to alienate low and medium-CLV customers because of the lower-level service provided and the differentiated treatment. Therefore, it is important for managers to determine the value of a customer's ability to spread word-of-mouth and make referrals. This chapter introduces and discusses the Customer Referral Value (CRV) metric for profitably managing customer referral behavior. By accounting for the attitudinal behavior of customers and measuring the indirect contribution (referrals or word-of-mouth) made by customers toward the firm's profit, this chapter shows that the CRV metric is the most appropriate metric for designing profitable referral strategies.

17.1 Optimal Resource Allocation Across Marketing and Communication Strategies

Customer equity is the aggregation of the expected lifetime values of a firm's entire base of existing customers and the expected future value of newly acquired customers (Hogan et al., 2002). A firm needs to make trade-offs that reserve strategic resources for the areas in which the expenditures will generate the greatest impact on customer equity (Rust, Zeithaml, & Lemon, 2000). The interpurchase time for a customer is influenced by marketing initiatives taken by a firm. A mathematical model for interpurchase time as discussed earlier in this book includes the frequency and nature of marketing and communication efforts. A model to predict the cash flows from each customer can be simultaneously developed. The net present value (NPV) objective function required to maximize the customer equity of a firm is related to the cash flow from each customer, the expected interpurchase time, and the cost and frequency of the marketing/communication strategies employed. A manager can determine the frequency of each of the available marketing and communication strategies such that the NPV objective function is maximized. An optimization technique can be utilized to accurately arrive at the differential allocation of strategic resources to individual customers across a variety of integrated marketing strategies (Venkatesan & Kumar, 2004). The objective function is thus based on three elements:

- A *probability-based model that predicts the interpurchase time* of each customer, as a function of marketing communication inputs and the customers' past purchase behavior observed over time.
- A *panel data model that predicts the cash flows* from each individual customer, also as a function of marketing communication inputs and the customers' past purchase behavior observed over time.
- An *optimization algorithm that maximizes the profits* from each individual customer by examining the impact of various levels of marketing communication inputs.

By applying an optimization model, a manager can know the extent to which he should use various contact channels. For example, for individual customers, should there be a decrease in face-to-face meetings and an increase in the frequency of direct mailers, or vice versa? Or, for segments of customers, how can total profitability over these segments be maximized? To illustrate the application of the optimal resource allocation procedure, it is useful to look at the results of a real-world situation.

First, it was necessary to establish that the model would do a good job of predicting whether a particular customer would buy in the next 12 months. Based on an analysis of a sample of 324 customers, out of 246 customers the model predicted would buy a product, 225 of them actually bought. Similarly, out of the 78 customers the model predicted would not buy the product, 66 of them did not buy. This suggests the model had a total accuracy, or hit rate, of 90% (see Table 17.1).

$$\text{Hit Rate} = 225 + 66 \div 324 = 90\%$$

Given this reassurance, we needed to examine if the customer value approach could eventually lead to an improvement in profits relative to the duration of association approach currently being employed by the firm to select customers and

Table 17.1 Effect of firm and market variables on the value of a lost customer

	Actually bought in the next 9 months	Actually did not buy in the next 12 months	Total
Expected to buy in the next 12 months as per the model	N = 225	n = 21	246
Not expected to buy in the next 12 months	N = 12	n = 66	78
Total			**324**

Table 17.2 Comparison of average profits in duration of association approach

	Duration of customer-firm association	
	Short	Long
Average profit per customer	$29,235(n = 170)	$141,655(n = 154)

Table 17.3 Customer value versus duration of customer-firm relationship

	Shorter duration		Longer duration	
Low customer value	*N* = 78	***Cell I***	*N* = 82	***Cell III***
	Average profit = $1387		Average profit = $1245	
High customer value	*N* = 92	***Cell II***	*N* = 82	***Cell IV***
	Average profit = $52,976		Average profit = $302,542	

prioritize its marketing action (Duration of association (one of the traditional measures of loyalty) indicates how long a customer has been transacting with the firm).

Table 17.2 shows the results of duration of association approach in terms of the classification of customers and their average profits.

The firm studied would break its customer base into two groups—short-duration customers and long-duration customers. Short-duration customers were those customers who had been transacting with the firm for less than a predetermined cut-off value of years. Consequently, the long-duration customers were the customers who had been transacting with the firm for longer than the cut-off value. From Table 17.2 it seemed as if they were doing the right thing, because the average profits from the short-duration group were much lower than the average profits from the long-duration group.

However, across analysis of duration of relationship and customer value, obtained on the basis of the NPV maximization objective function, indicates not all short-duration customers deliver lower profits, and not all long-duration customers deliver higher profits. A superior approach could be thus adopted by identifying and targeting responsive and profitable customers and by deemphasizing efforts on some customers who were not profitable, irrespective of whether they are classified as long-duration or short-duration customers. Some of the profitable customers had escaped the firm's attention when only the duration of association approach was being followed. Also, the firm was allocating disproportionately higher resources to some long-duration customers in the mistaken belief that the duration of their association with the firm was indicative of their profitability (see Table 17.3).

The observations in *Cell III* indicate more than 50% of the customers that the firm was chasing in the long-duration segment were actually low-value customers. The observations in *Cell II* indicate the firm was ignoring a sizable set of customers by classifying them as short-duration customers, when indeed they were contributing significantly to profits. Thus, the customer value-based approach demonstrated its superiority to the duration of association approaching terms of profitable segmentation of customers. By using the optimal resource allocation model, we can improve profitability in each of the cells as shown in Fig. 17.1.

The analysis recommends changing the frequency of face-to-face meetings, direct mail, and telesales in each cell to an optimal level, thereby enhancing the effectiveness of the marketing/communication initiatives. By changing over to the optimal frequencies, recommended by the model for face-to-face meetings and direct mail telesales, in each of the four cells, a 10% decrease in overall costs and a 6% increase in overall profits were observed.

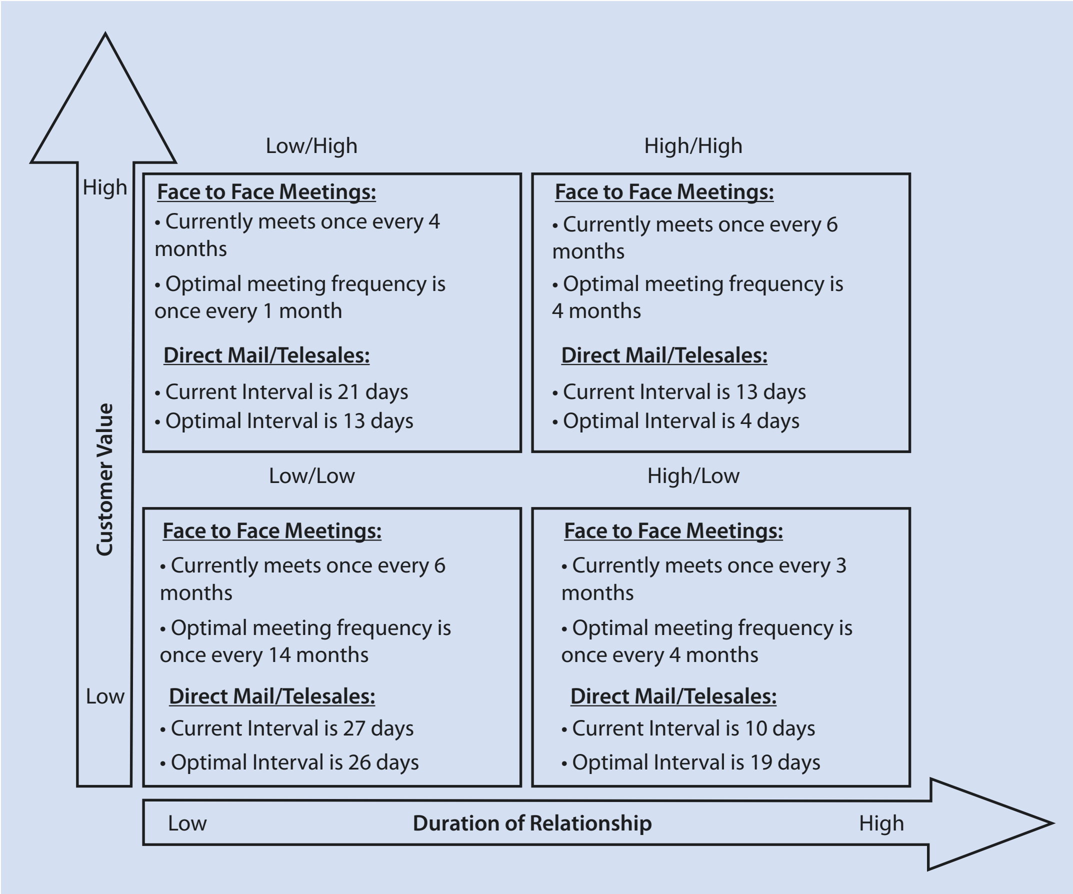


Fig. 17.1 Reallocation of resources based on customer value (all figures have been altered by a constant multiplier for confidentiality reasons)

17.2 Purchase Sequences Analysis: Delivering the Right Message to the Right Customer at the Right Time

In the case of a multiproduct firm, it is important to understand which product in the portfolio is likely to be needed next by a customer. An ideal contact strategy is one where the firm is able to deliver a sales message relevant to the product likely to be purchased in the near future by a customer. The next level is therefore the development of a *purchase sequence model*.

A purchase sequence model (Kumar, Venkatesan, & Reinartz, 2004) addresses three questions:

- What is the sequence in which a customer is likely to buy multiple products or product categories?
- When is the customer expected to buy each product?
- What is the expected revenue from that customer?

This model captures the differences in the durations between purchases for different product categories. The interdependence in purchase propensities across products is modeled by incorporating cross-product category variables. An individual customer level profit function is developed to predict customer value. To demonstrate such a model delivers superior results in the field, an experiment was set up in the sales department of a high technology B2B vendor, which markets multiple categories of products.

The model was developed for the hardware products of the firm. The model is able to prioritize

Table 17.4 Change between current year and previous year

	Test group	Control group
Revenue ($)[a]	1050 (18,130)	1033 (17,610)
Cost of communications ($)	−750 (3625)	75 (4580)
Number of attempts before purchase	−4 (15)	1 (18)
Profits ($)	3000 (9080)	637 (6275)
Return on investment (%)	5.4 (3.7)	2.2 (2.0)

Note: Number indicates change from base level (previous year). Base level is in parentheses
[a]The reported values are unit values per customer

Table 17.5 Difference in performance between test and control group

	Difference between test and control group
Revenue ($)[a]	537
Cost of communications ($)	−1780
No. of attempts before purchase	−8
Profits ($)	5168
Return on investment (%)	4.9

[a]Number indicates change from base level the previous year. Base level is in parentheses. The reported values are unit values per customer.

customers by indicating the propensity to purchase different hardware products for each of its customers. It also predicts the expected profits. Empirical evidence from this experiment suggests profits predicted on the basis of a purchase sequence model are accurate and that using the model results in a greater return on marketing investments. Table 17.4 is an illustration of the improvement for the hardware category, over the previous year, in profits generated by the test group of salespersons who adopted strategies based on the outcome of the purchase sequence model versus the control group of salespersons not provided the predictions given by the model.

As Table 17.4 shows, there is a significant decrease in the cost of communication resulting in a saving of $750 on last year's base of $3625. In comparison, the control group saw an increase in its cost of communication by $75 on an already high last-year base of $4580. The test group was able to reduce the average number of attempts before purchase by four, whereas for the test group this number increased by one, compared to the respective figures for last year. Similarly, for the test group, profits were higher and so was ROI.

Table 17.5 provides the difference in performance between the test group and the control group.

We see again during the experiment period, the test group revenue is higher, cost of communication is lower, number of attempts before a purchase is made is lower, profits are higher, and ROI is higher, when compared to the control group. The success of the experiment indicates the scope that the customer value approach offers in improving the quality of marketing decisions.

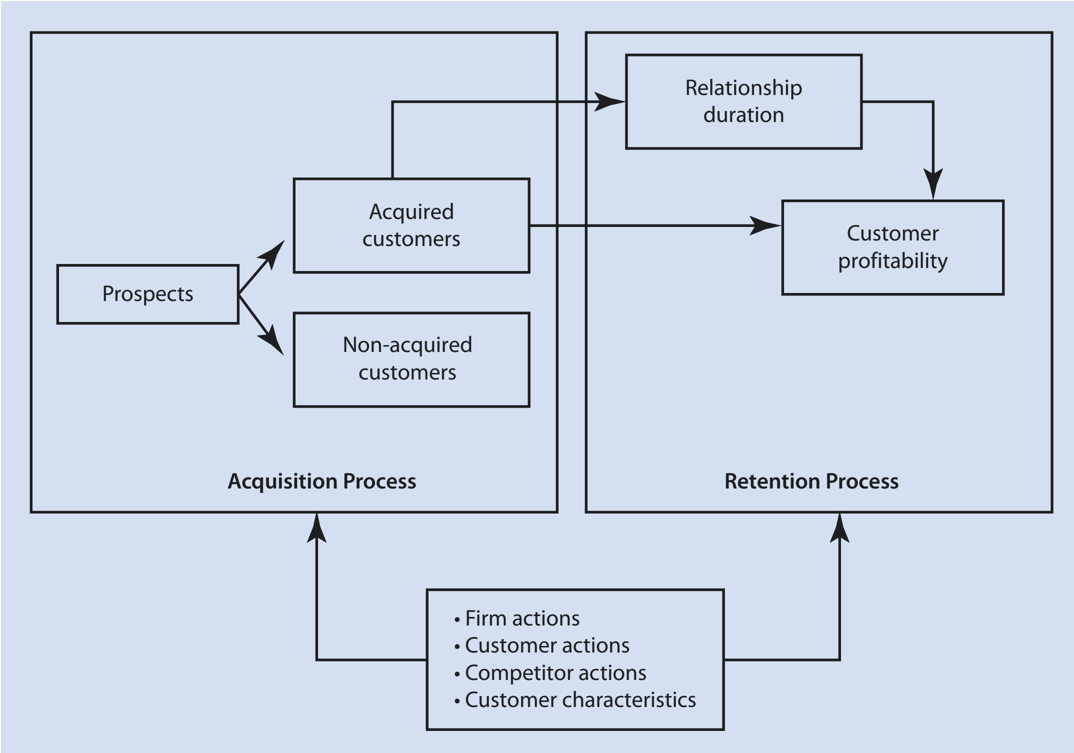


Fig. 17.2 Linking customer acquisition, relationship duration, and customer profitability

17.3 The Link Between Acquisition, Retention, and Profitability: Balancing Acquisition and Retention Resources to Maximize Customer Profitability

Measuring, managing, and maximizing customer profitability is not an easy task. From a marketing resource allocation perspective, it requires a manager to (1) set a budget, (2) balance how much to spend on customer acquisition and customer retention, and (3) determine how the expenditures are allocated between contact channels. The objective is, of course, to maximize a customer's long-term profitability. For example, a manager of a paper company distributes sales force efforts and directs marketing efforts among its set of 350 business customers. The manager also has to constantly juggle how many new prospects should be targeted at a given point in time vis-à-vis the portion of time and effort to be directed to existing customers. In this section, we summarize the findings of a study that examines these questions (Reinartz, Thomas, & Kumar, 2005).

In contrast to most other studies, the acquisition process is an integral component of the research model. The conceptual link between the acquisition and the retention process is important for two reasons. First, only by linking the two, one can see a complete and unbiased picture of the drivers behind customer selection/acquisition, relationship duration, and customer profitability (See Fig. 17.2) (Heckman, 1979).

Prior research has specifically shown that a failure to link acquisition and retention can lead to biased results and incorrect inferences (Thomas, 2001). This is due to the selection bias resulting from the omission of information on no acquired prospects. Second, offensive processes and defensive processes compete for the same resources. Making the necessary trade-off requires a full specification of the key dimensions of the customer-firm relationship. Thus, a more complete model specification allows us to address a key managerial question: «Does the maximization of the respective objective functions (a.k.a, acquisition likelihood, lifetime duration, and customer value) lead to convergent or divergent resource allocation recommendations? ».

It is important to note this model applies mainly to situations where managers mostly rely on direct customer communication, such as via sales force, direct mail, or Internet. This is the case for most B-to-B environments, as well as for many direct marketing contexts.

The interest of this study lies mainly in the impact of (1) amount of spending and (2) contact channel type on three dependent variables: acquisition rate, retention rate, and customer profitability.

As firms increase their acquisition budget, the associated acquisition rate and customer profitability will be less and less responsive (concavity). Even if, for all practical purposes, there were no limits on acquisition expenditure, firms are able to capture only a certain share of the potential targets. We can expect that acquisition expenditures will have diminishing marginal associations with the likelihood of customer acquisition. Also, acquisition expenditures will have diminishing marginal associations with customer profitability. Similarly we can see that increasing retention expenditures will cease to be profitable beyond a certain level. Thus, we can expect retention expenditures will have diminishing marginal associations with relationship duration and with customer profitability.

We would also like to see if the nature of the contact channel affects acquisition and relationship duration. We can expect highly interpersonal contact channels have a greater association with the likelihood of customer acquisition than less interpersonal contact channels. Also, highly interpersonal contact channels have a greater association with relationship duration than less interpersonal contact channels.

At the most simple level, different contact channels may be seen as having independent effects on the respective dependent variables, acquisition, duration, and customer profitability. However a potential interaction effect between channels is likely to exist. For example, one could argue that contacting a prospect via telesales and via direct mail at the same time may have a stronger effect than the sum of the separate effects administered at different points in time. This is due to the mutual reinforcement of the message delivered through the different contact channels at the same time.

The empirical context for this research is the same B-to-B firm as in the previous two examples. The following substantive conclusions emerge from this empirical context:

- The *amount of investment* in a customer as well as *how it is invested* has an impact on acquisition, retention, and customer profitability.
- Investments into customer acquisition and retention have diminishing marginal returns.
- How much is invested in a customer-firm relationship has a larger impact on long-term customer profitability than how the expenditures are invested across communication channels. Thus, optimizing the amount of relationship investment is of prime importance.
- The relative effectiveness of highly personalized communication channels is much greater than the less personalized communication channels. However, the relative cost also needs to be taken into account when deciding the communication strategy as it affects the overall profitability.
- Under spending in acquisition and retention is more detrimental and results in smaller ROIs than overspending.
- When trading off between allocating expenditures to acquisition versus retention, a suboptimal allocation of retention expenditures will have a larger detrimental impact on long-term customer profitability than suboptimal acquisition expenditures.
- The customer communication strategy that maximizes long-term customer profitability maximizes neither the acquisition rate nor the relationship duration. Instead, developing a communication strategy to manage long-term customer profitability generally requires a long-term and holistic perspective of the relationship. This perspective tends to give more emphasis to more interpersonal and interactive communications than a limited focus on acquisition.

Although the results are specific to the empirical context, the model can be applied to any environment where acquisition and retention efforts can be separated. Managers can use the proposed integrated framework not only to better understand the drivers of profitability, but also to know how to maximize profitability through optimal allocation of resources.

17.4 Preventing Customer Churn

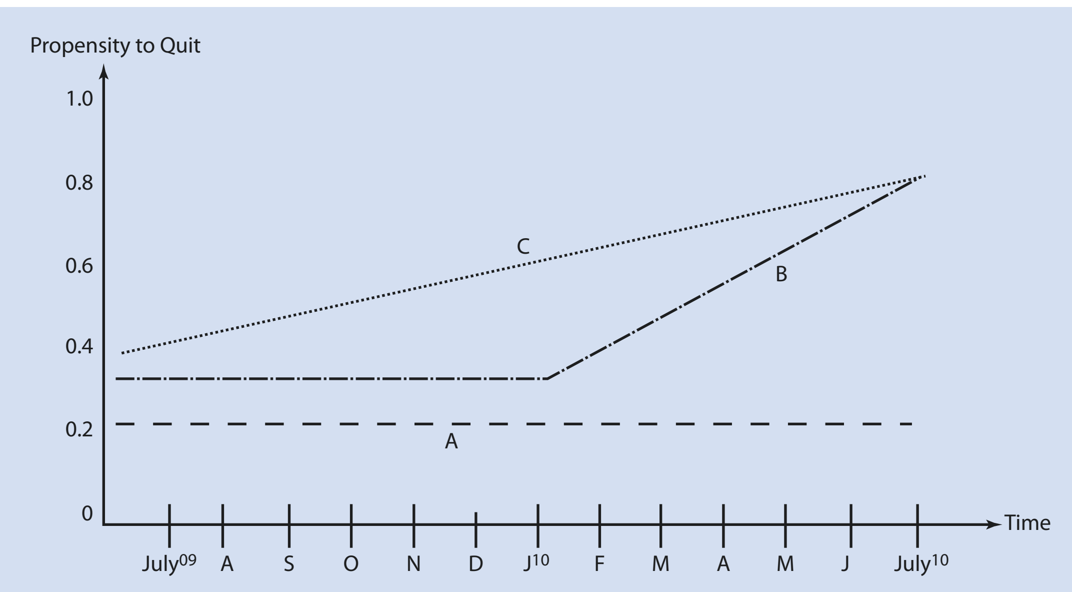
Customer retention is a crucial function for any organization. When customers churn and end the relationship, it impacts the firm in several ways. First, the firm incurs a loss of revenue from the customers who have defected. Second, the firm loses the opportunity to recover the acquisition cost incurred on the defected customers, thereby increasing the pressure to break even. Third, the firm loses the opportunity to up-sell/cross-sell to customers who have defected, and this loss can be treated as a loss of potential revenue. Fourth, there are some «lost» social effects such as influencing other customers on product/service adoption and a potential negative word-of-mouth. Finally, firms must also invest additional resources to replace those lost customers with new customers, thereby draining the firm's resources already impacted by the loss of customers.

Given these potential problems of losing customers, it is essential for companies to adopt appropriate analytical tools to prevent customer churn. Analytical 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:

- Should we intervene?
- Which customers should we intervene with?
- When do we intervene?
- Through which channel do we intervene?
- What do we offer them?

These critical questions can be answered by 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 Customer A, Customer B, and Customer C. The predicted propensity-to-quit of the three customers over time (July 2009–July 2010) is illustrated in ◘ Fig. 17.3.

As shown in ◘ Fig. 17.3, Customer A does not intend to quit 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 2010. Customer C, represented by a steep curve, shows a strong tendency to quit from early on. Clearly, this indicates



◘ **Fig. 17.3** Predicting propensity to quit

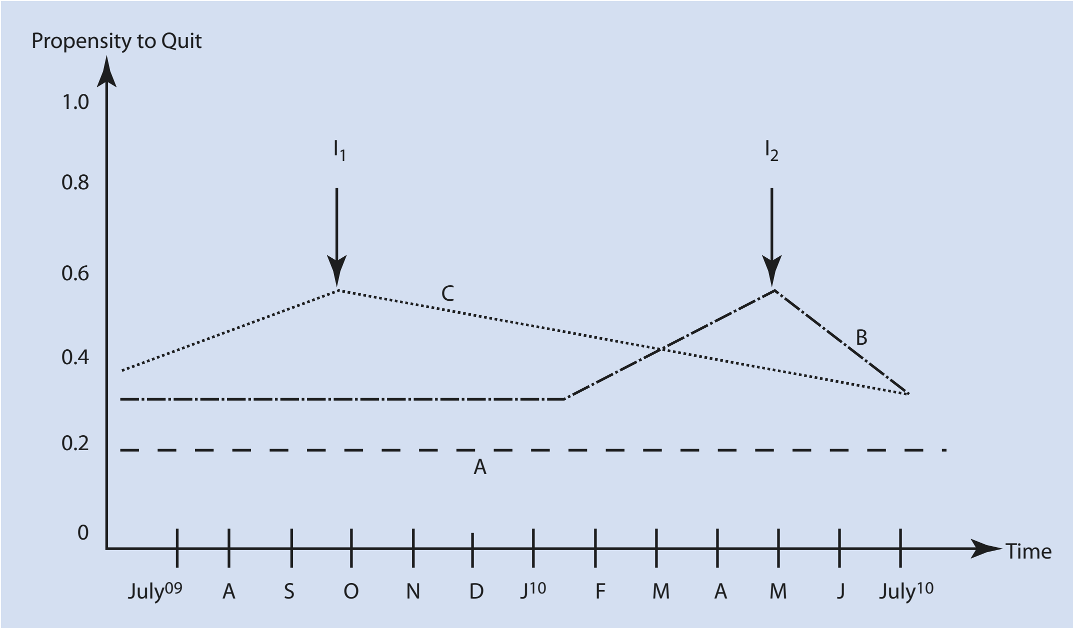


Fig. 17.4 Proactive intervention strategy

that Customers B and C are likely to quit in the near future and they are the customers to be intervened with.

Once the need to intervene and the customers to be intervened with 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. That is, the customers who show a strong tendency to quit (in this case Customers B and C) should be targeted with intervention offers by the firm. Figure 17.4 shows the time periods in which Customers B and C should be intervened with.

In Fig. 17.4, points I_1 and I_2 denote the intervention points when customers B and C should be intervened and this is followed by a decrease in propensity to quit on the part of the customers. Here, Customer B is being intervened with in May 2010 and Customer C in October 2009. The reason for the time lag between the customer intervention stems from their respective propensities to quit. So, while Customer C is intervened with early on, Customer B can be intervened with at a later stage.

The decision on the channel of intervention and the type of offer through which the intervention is to be made is based on individual customer characteristics. The amount of resources to be spent on each customer is directly linked to the Customer Lifetime Value. If it costs the company $100 per customer to intervene with, it is not prudent to promote to a customer whose CLV is only $50. The company should intervene with an offer that costs less than $50. Thus, proactive intervention strategies help companies to pre-empt customer attrition and thereby increase ROI.

This strategy to prevent customer attrition was tested in a recent study for a telecommunications firm (Kumar & George). The firm first computed the propensity to quit for all its customers using 3 years of transaction and marketing communication data. Then, they created two groups of matched customer pairs who were similar in terms of their propensity to quit and the exchange characteristics such as their revenue contribution to the firm and duration. In other words, the customers in both groups had the same probability of quitting.

The average revenue per customer in both groups was $600 per year. The test group had 2601 customers and the control group had 2602 customers. There was no intervention for the control group and this group was used to see the impact of intervention on the test group. For all customers in the test group, however, the firm predicted propensity to quit and identified those customers who are likely to quit.

Based on the CLV of each customer, the firm designed customer-specific intervention strategies for all vulnerable customers. The total cost of intervention for the firm was $40,000 for the test group. The intervention saved 643 customers for the firm. By multiplying the number of customers by the average revenue contribution per customer, the total revenue gain was $385,800 for the group that was intervened. Thus, even after taking into account the cost of intervention, the firm had a net revenue gain of $345,800 by preventing attrition and the return on investment was close to 860% (i.e., the revenue contribution was 8.6 times the investment).

From the above study, it is clear that churn models help firms to identify the customers who are likely to quit, the intervention strategy based on CLV helps to effectively intervene to retain valuable customers. In this regard, targeting profitable prospects is an important planning phase for firms. Accurate customer profiling analysis helps firms implement a solid marketing strategy. Firms should target prospects precisely by choosing segments that match the firm's customer base and channels that match the customer's preferences. Additionally, 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.

17.5 Customer Brand Value

In our everyday lives, we come across different brands that we use. We perceive some brands as very high and some brands as very low. Why does this happen? Ideally, brands are developed to perform three important roles—(a) to draw new customers to the firm, (b) to remind existing customers about the products/services it offers, and (c) to forge an emotional attachment with its consumers (Rust, Lemon, & Narayandas, 2004). When brands start to perform poorly on one or more of these roles, it starts to lose its sheen and falters.

When a brand starts to face such hiccups, the brand manager or the marketing manager, and in some cases the entire corporate board faces some dilemma. Some of these questions include: (a) What do we invest on—building brands or building the customer base? (b) How do we manage the brand? (c) What can we do to renew our relationship with our customers? The single answer to all these questions is to strengthen the brand and nurture profitable customer relationships simultaneously. How can we achieve this?

We can strengthen a brand by ascertaining and increasing the value a customer provides to the brand. This is value is referred to as CBV. And, we have already seen in the previous section that CLV can help firms in managing customer relationships profitably. Therefore, by establishing a link between CBV and CLV, we can strengthen the brand and build profitable relationships simultaneously. This section provides an approach to determine CBV and also designs an approach that will link CLV and CBV in order to ensure simultaneous growth in brand equity and customer equity.

17.5.1 What Is Customer Brand Value?

The concept of CBV refers to the differential effect of an individual's brand preference on his/her response to the marketing of a brand. It comprises of eight constructs (Kumar, Luo, & Rao, 2008). They are:

- **Brand knowledge:** Made up of a customer's awareness of the brand (brand awareness) and a customer's image of the brand (brand image).
- **Brand attitude:** Made up of a customer's trust in the brand (brand trust) and a customer's emotional response towards the brand (brand affect).
- **Brand behavior intention:** Made up of a customer's intention to purchase a brand (purchase intention).
- **Brand behavior:** Made up of a customer's repeat-buying behavior (brand loyalty), relationship with other customers of the brand (brand advocacy), and willingness to pay a price premium over other brands (brand price premium behavior).

Based on these eight constructs, it has been found that customers with greater brand value are more likely to engage in activities that result in an increase of customer lifetime value when compared to customers with low brand value. Intuitively, we can understand that an individual customer's brand knowledge, brand attitude and brand behavior intentions affect his/her brand purchase behavior. When this brand purchase behavior of a customer is linked to their lifetime value, a firm can expect to maximize profitability. This brings us to the next question, how do we link CBV and CLV?

17.5.2 Linking Customer Brand Value to Customer Lifetime Value

The link between CBV and CLV is established using customer-level data and advanced modeling techniques. The customer-level data is important to compute CLV and CBV. We have already seen that data for computing CLV can be secured from the customer transaction database within the company. To compute CBV, firms can get information regarding the various components of CBV from survey data. A survey that contains questions pertaining to the eight constructs can yield the firm information that is necessary for computing CBV. Once this information is available, the next step is to estimate how these components affect each other by using sophisticated estimation techniques. The components of CBV are obtained using a ten-point scale from a sample of customers. For the same customers, CLV is computed at that time. Conceptually, the CLV score is modeled as a function of these eight constructs.

17.5.3 What Are the Managerial Benefits of Linking Customer Brand Value to Customer Lifetime Value?

There are three key implications of linking CBV to CLV. They are:

Monitor the Overall Performance of Customer Brand Value

This linkage can help firms to monitor the overall performance of CBV. 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 to improve or positively influence them.

Manage Brand at the Segment Level

In order to manage the brand at a segment level, firms can segment customers based on CBV and CLV. This would yield a matrix with four cells, very similar to the «Managing loyalty and profitability simultaneously» strategy of CLV (refer ► Chap. 15). Here, we can segment high CLV-high CBV customers as «True Loyalists»; high CLV-low CBV customers as «Acquaintances»; low CLV-high CBV as «Poor Patrons»; and low CLV-low CBV customers as «Strangers».

The marketing strategy for «True Loyalists» is to keep building positive brand knowledge and attitude with this segment of customers. For the «Acquaintances» segment, firms should think of other ways to increase their CLV with limited brand investment. With regard to the «Poor Patrons» segment, firms should moderately invest to improve the brand values in this segment. They can encourage cross-buy and add-on selling to increase the customers' CLV values. Finally for the «Strangers» segment, firms should invest moderately on the strangers who have the potential to increase their CLV values.

Manage Brand at the Individual Level

Firms can also manage brands at the individual customer level. We saw in the «Managing loyalty and profitability simultaneously» strategy of CLV that «True friends» are the most valuable asset of a company. Therefore, 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 CBV can be simultaneously maximized.

Until now, we have seen how a customer can provide value to a firm through his/her purchases and to a brand through his/her preferences towards the brand. These two sources of value originate directly from the customers. However, a customer can also provide indirect value to a firm through his/her referrals or positive word-of-mouth. The next section discusses the Customer Referral Value metric, its measurement and strategies to maximize it.

17.6 Customer Referral Value

Many firms now use viral marketing programs to harness the power of word-of-mouth and referrals to acquire new customers. Typically, satisfied customers provide referrals and positive WOM to their friends or associates. Some of these referred customers will have the potential to be profitable customers of the firm. Consequently, a customer's CLV for a firm will not only be the profits they contribute but also the profits resulting from those they influence. This indirect value that a customer brings in through referrals is measured by the CRV metric.

We have seen that the CLV metric is a superior customer value metric over all the conventional metrics. However, the treatment this metric gives to customer satisfaction is not so complete. While it is true that the customer satisfaction information is captured by accounting for customer buying behavior, it does not involve a direct measurement. It is clear that customers can not only contribute value to the firm through their own transactions (direct profits), but they also have an impact on the transactions of other customers through word-of-mouth and referrals (indirect profits) by helping the firm to acquire new customers at lower costs. Therefore, we need a metric such as CRV to determine the value of a customer's ability to spread word-of-mouth and make referrals.

17.6.1 What Is Customer Referral Value?

Customer Referral Value is defined as a customer's expected future referral value with the firm. This metric enables managers to measure and manage each customer based on his ability to generate indirect profit to the firm. This indirect impact on the firm's profit comes through savings in acquisition costs and through the addition of new customers by way of customer referral.

Calculating customer referral value (CRV) is more complex than calculating the lifetime value. Consider a customer, Jane, for whom we will compute the referral value. First, we need to compute the average number of successful referrals she will make after we offer her an incentive to do so through a marketing campaign. As we do for her CLV, we look at Jane's past behavior, but we need to look at a period longer than a month to get enough variance in the number of referrals for proper statistical modeling and predictive accuracy. The time period varies from industry to industry.

Then, we need to estimate the time frame for which our marketing campaign has an impact in generating referrals. In other words, we need to determine the time until which Jane's referrals are actually prompted by our referral incentive. In research studies, it has been found that this time period is about 1 year. That is, referrals made by customers after a referral-incentive marketing campaign can be attributed to that campaign for about a year. Therefore in computing CRV, we count only those referrals that are made within a year.

Then, we need to determine how many of those referrals would have become customers of the firm anyway, even if Jane had not recommended the firm. The reason for determining this is simple. If a new customer, let's call him John, would not have joined without Jane's referral (referred to as a type-one referral), then Jane's referral value should include the value of John's business. However, if John would have become a customer without Jane's referral (referred to as a type-two referral), then, Jane's CRV should include only the savings in acquisition costs for John, since no direct marketing effort was needed to get him. Obtaining this information can be done through surveys by asking a simple question such as: «How likely is it that you would have purchased our product/service without a referral in the next 12 months?».

After collecting this information, we can compute Jane's referral value as the present value of her type-one referrals plus the present value of her type-two referrals. Therefore, if we assume that if John would not have become a customer had Jane not referred him, then, Jane's type-one referral of John is essentially the same as his lifetime customer value—the present value of the difference between John's contribution to margin and the cost of marketing to him, projected over 1 year. Consequently, the value of type-two customers is the present value of the savings in acquisition costs. As with all cost-revenue analyses, if the cost involved in acquiring type-two referrals exceeds the cost of alternative acquisition methods, type-two customers can be a liability for the firm. Therefore, the CRV formula can be expressed as follows:

$$CRV_i = \sum_{t=1}^{T}\sum_{y=1}^{n1}\frac{\left(A_{ty} - a_{ty} - M_{ty} + ACQ1_{ty}\right)}{(1+r)^t} + \sum_{t=1}^{T}\sum_{y=n1}^{n2}\frac{\left(ACQ2_{ty}\right)}{(1+r)^t} \quad (17.1)$$

Where:

T = the number of periods that will be predicted into the future (e.g. quarters, years).

A_{ty} = the gross margin contributed by customer «y» who otherwise would not have bought the product.

a_{ty} = the cost of the referral for customer «y».

1 to n1 = the number of customers who would not join without the referral.

n2 – n1 = the number of customers who would have joined anyway.

M_{ty} = the marketing costs needed to retain the referred customers.

$ACQ1_{ty}$ = the savings in acquisition cost from customers who would not join without the referral.

$ACQ2_{ty}$ = the savings in acquisition cost from customers who would have joined anyway.

In simple terms, (17.1) can also be expressed as follows:

$$CRV_i = \frac{\text{Value of customers who joined because of referral}}{\text{Discount rate}} + \frac{\text{Value of customers who would join anyway}}{\text{Discount rate}} \quad (17.2)$$

Having seen the concept and measurement of CRV, let us actually compute the CRV of a customer from a hypothetical financial services company.

17.6.2 How Can Compute Customer Referral Value Be Computed?

In order to value customers and see how they truly impact the bottom line of the company, let us consider a typical customer—Tom, from a financial services company. Using this customer's

Table 17.6 Tom's referral behavior in a financial services company (semi-annual data)

Number of referrals per period (n_2)	4
Marketing cost per period (M_{ty})	\$18
Average gross margin (A_{ty})	\$98
Cost of referral (a_{ty})	\$40
Acquisition cost savings ($ACQ1_{ty}$ and $ACQ2_{ty}$)	\$5
Number of referrals that would have joined anyway ($n_2 - n_1$)	2
Yearly discount rate (r)	15%

referral behavior data from the company, we will compute his referral value (CRV). The data we need to compute the referral value is provided in Table 17.6.

There are four steps involved in the computation of CRV. They are:

Step 1: Purchase

In the first step, we determine whether customers would have made purchases anyway. As is evident from Table 17.6, Tom refers four customers per period (6 months) and of those four customers, two would have joined anyway. So, n_1 in this case is two and n_2 in this case is four. For the purpose of illustration, we consider here only the value of those customers who were directly referred by Tom and made a purchase. This approach can also be extended to include the value brought in by customers who were indirectly referred by Tom, wherever applicable.

Step 2: Future Value

In the second step, we predict the future value of each referred customer. The future value of each referred customer is based on that customer's gross margin per period (\$98), marketing cost per period (\$18), acquisition cost savings (\$5), cost of referral (\$40), and discount rate (15% annually).

Step 3: Number of Referrals

In the third step, we predict the number of referrals generated. The number of referrals predicted for Tom is four per period. Because we are measuring CRV for 1 year, Tom will generate a total of eight referrals.

17

Step 4: Timing of Customer Referrals

In the final step, we predict the timing of customer referrals. Since, Tom refers four customers per period, in terms of timing this means that four customers are referred in the first half of the year and four customers are referred in the second half of the year.

Applying these steps for the data we have for Tom, we get the following:
For Period 1:

$$\mathrm{CRV}_1 = \sum_{y=1}^{n1} \frac{\left(A_{1y} - a_{1y} - M_{1y} + ACQ1_{1y}\right)}{(1+r)^1} + \sum_{y=n1+1}^{n2} \frac{\left(ACQ2_{1y}\right)}{(1+r)^1}$$

$$\mathrm{CRV}_1 = \sum_{y=1}^{2} \frac{(\$98 - \$40 - \$18 + \$5)}{(1+0.075)^1} + \sum_{y=3}^{4} \frac{(\$5)}{(1+0.075)^1} \approx \$93 \quad \textbf{(17.3)}$$

For Period 2:

$$\mathrm{CRV}_2 = \sum_{y=1}^{n1} \frac{\left(A_{2y} - M_{2y}\right)}{(1+r)^2} + \sum_{y=1}^{n1} \frac{\left(A_{2y} - a_{2y} - M_{2y} + ACQ1_{2y}\right)}{(1+r)^2} + \sum_{y=n1+1}^{n2} \frac{\left(ACQ2_{2y}\right)}{(1+r)^2}$$

$$\mathrm{CRV}_2 = \sum_{y=1}^{2} \frac{(\$98 - \$18)}{(1+0.075)^2} + \sum_{y=1}^{2} \frac{(\$98 - \$40 - \$18 + \$5)}{(1+0.075)^2} + \sum_{y=3}^{4} \frac{(\$5)}{(1+0.075)^2} \approx 225 \quad \textbf{(17.4)}$$

$$\text{Total CRV} = \mathrm{CRV}_1 + \mathrm{CRV}_2 \approx 318$$

Therefore, the total CRV for Tom for 1 year is the sum of CRV_1 and CRV_2, which is around \$318. As the results show, the impact grows as time progresses. The main reason for this is the growth of the customer base due to referrals in each period. In period 1, there were only four new customers, whereas in period 2 there were six customers in the value of the CRV (four new customers and two customers from period 1 who bought only because of the referral).

As mentioned already, because this is a conservative estimate of the value of customer referrals (that is, only the direct referrals are used in the CRV), it does not provide a true picture in terms of the number of new customers whohave been acquired by the firm and the total value all these new customers are worth to the firm. If we want to see how many new customers came on board over these two periods that stem from the original customer and the value of these new customers, we need to look at both the direct and the indirect referrals (For more information on direct and indirect referrals see Kumar & Bhaskaran, 2010). If each of the customers who were referred during a specific period also made some referrals in subsequent periods, we would see an exponential growth in the total number of new customers who were acquired in the two periods and the total CRV for those customers. Given that CRV also considers the net present value brought in by a customer, one might wonder how CRV is linked with CLV. The following section provides the linkage.

17.6.3 How Can Customer Referral Value Be Linked to Customer Lifetime Value?

Once the CRV of customers has been computed, it is essential for managers to understand the relationship it shares with CLV. Now that we have a measurement for both CLV and CRV, we know the value provided by the actual purchases made by the customer (CLV) and the influence that customer has on other potential customers (CRV). With this information, managers can begin to make decisions about how to treat and market to customers based on the various combinations of whether the customer is low or high on CLV or CRV.

As noted previously, many firms are using CLV as a method for selecting customers for word-of-mouth and referral campaigns. If the customers who rated highly on CLV were the same customers who rated highly on CRV, managers would not need to use both metrics when managing customers. However, because only transactional and demographic data (not attitudinal data) has played an important role in predicting CLV, customers who score highly on CLV are probably not the same as those who are successful at referring new customers. In fact, a recent marketing study found that customers who score high on CRV are not the most valuable customers, as determined by CLV. This study used the transaction and referral behavior data from a telecommunications firm to investigate the link between CLV and CRV. The findings of the study are provided in Table 17.7 (Kumar, Petersen, & Leone, 2007).

As is evident from Table 17.7, the top 30% of the customers ranked on the basis of CLV (deciles 1, 2 and 3) have no overlap with the top 30% of customers based on CRV (deciles 5, 6, and 7). This finding provides managers important insights on customer management. If managers ignored the concept of CRV and focused only on CLV, then they would miss out on the positive WOM and the cascading business it would generate. Consequently, if they focused only on CRV and ignored high CLV customers, they would be alienating the most valuable customers for want of positive WOM. Any of these two scenarios can cause much harm to customer growth and, in some cases may even generate negative WOM.

Table 17.7 Customer deciles of CLV and CRV for a telecommunications firm

Deciles (ranked by CLV)	CLV ($) (1 year)	CRV ($) (1 year)
1	**1933**	40
2	**1067**	52
3	**633**	90
4	360	750
5	313	**930**
6	230	**1020**
7	190	**870**
8	160	96
9	137	65
10	120	46

Source: Adapted from Kumar et al. (2007)

17.6.4 What Are the Managerial Benefits of Linking Customer Referral Value and Customer Lifetime Value?

To show the impact of measuring and managing these two metrics simultaneously, a field study was conducted with the telecommunications firm to see the benefits of measuring and managing CLV and CRV simultaneously.

For the purpose of the field study, a test group and a control group of 9900 customers each were considered.CLV and CRV were measured for each of the groups. Based on these two values, the customers in both groups were divided into four cells of a 2 × 2 matrix. The cells were segmented on the following basis—high CLV/high CRV, high CLV/low CRV, low CLV/high CRV, and low CLV/low CRV. The cutoff points for the four segments were determined based on the median value for both the CLV and CRV measures. Figure 17.5 summarizes these results.

Of the sample of 9900 customers, the «Misers» and «Champions» segments had 2079 customers each, and the «Affluents» and «Advocates» segments had 2871 customers each. These findings also validate the findings presented in Fig. 17.5 that high CLV and high CRV customers are distinct sets of customers. The results of this measurement of CLV and CRV show that there are distinct sets of customers found in the four different cells based on the large differences in the values for CLV and CRV across the cells. Further, it has to be noted that there exists a significant difference between the customers who are high on the CLV measure and those who are high on the CRV measure. Now, let us consider each of the cells separately.

The «Affluents», or the high CLV/low CRV customers, purchase a lot of products and services for themselves, but they do not refer many new customers to buy products and services. On the contrary, the «Misers», or the low CLV/low CRV customers, do not purchase much or refer many new customers. Their low purchase behavior may be due to frequent brand switching, small SOW or they might be waiting to find out from others whether the product is worth purchasing.

The «Advocates», or the low CLV/high CRV customers, do not exhibit a high purchase behavior for themselves. However, they are

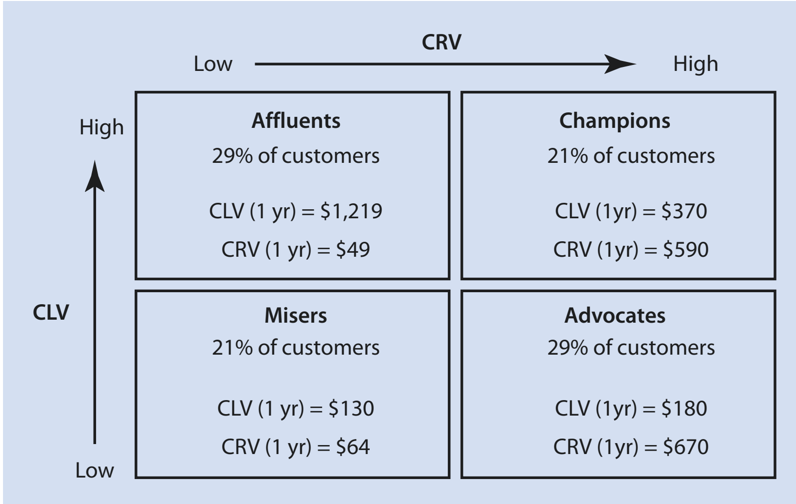


Fig. 17.5 CLV-CRV matrix for a telecommunications firm

Table 17.8 Campaign for «Misers», «Advocates» and «Affluents» for a telecommunications firm

Campaign for «Misers»	Campaign for «Affluents»	Campaign for «Advocates»
Targeted with bundled offers for one or more products	Targeted with emphasis on the referral incentive for both them and the referred customers	Sent personalized direct mail communication that included offers for bundling one or more products
Personalized communication sent via direct mail and followed up with another direct mail piece within a 2-week period	Contacted through a direct mail communication, followed by another direct mail communication within 2 weeks	Follow up communication was sent through direct mail within 2 weeks
Telephone assistance for those customers on questions regarding additional services and the value of obtaining the additional services	Emphasized a $20 incentive for both the referral and the referring customer for signing up for products and/or services	Contacted a sample of these customers via the telephone to answer any questions regarding the additional services and the value of subscribing to multiple products/services
Value of making referrals was highlighted for these customers and a $20 incentive was offered to them for making a referral		

actively involved in talking about the product to other customers and encouraging them to buy products. Finally, and true to their name, «Champions», or the high CLV/high CRV customers, are more likely to buy more products/services from the company and talk more about them to other customers.

Given the vast differences between the four cells, the customers in each of the cells should be evaluated differently with respect to their total value to the company and then approached with different types of marketing offers to get the greatest overall value from them. To understand the true value of treating customers differently, the telecommunications firm initiated three different campaigns over the course of 1 year in an effort to migrate customers from low CLV/CRV cells to high CLV/CRV cells. These campaigns were administered to the sample customers from the test group. The control sample did not receive any of these targeted marketing communications. Table 17.8 summarizes these campaigns.

It is clear from Table 17.8 that each of the three campaigns was designed with a different goal in mind. The campaign for the «Misers» was designed to help the company identify opportunities of building a relationship with them. This campaign not only offered incentives for them to buy more products for their own use, which would increase their CLV, but also offered them incentives to refer new customers, which would increase their CRV. The goal of this campaign was to migrate them toward one of the other three cells («Affluents», «Advocates», or «Champions»), depending on whether the campaign increased their CLV, their CRV, or both.

The campaign for the «Affluents» was launched to encourage referral behavior using referral incentives, while retaining their CLV at the highest level. And when their referral value increases, it will cause them to migrate toward the «Champions» cell. Additionally, this will also increase the average CLV of the «Champions» cell over time, as the «Affluents» bring their high CLV with them. Similarly, the campaign for the «Advocates» was designed to encourage these customers to spend more while at the same time keeping their CRV at the highest level. The company could potentially gain a higher direct profit from these customers by migrating them to the «Champions» cell.

So, what was the result of all these campaigns? The study tracked the three segments individually and monitored their performance. At the end of 1 year, the company realized impressive results from these campaigns. Table 17.9 presents the results of the campaigns.

From Table 17.9 it is clear that the goal to migrate customers was achieved. After administering the campaign, the number of customers in the «Misers» segment decreased from 21% to 9%. Of the 12% who migrated to other segments, 4% of the customers went to the «Affluents», «Champions» and «Advocates» segments each. The gains from this migration were also substantial. The average CLV of the «Affluents», «Champions» and «Advocates» increased by 185%, 138% and 422% respectively. Additionally, the «Champions» segment also witnessed a 328% increase in its average CRV. In actual numbers, of the original sample of customers from the «Misers» cell (2079 customers), 396 of them moved toward «Champions» and produced increases of CLV of $71,280 and CRV of $83,160. While these numbers may seem small, this would produce huge numbers when projected to the entire customer base of the company.

With respect to the «Affluents» segment, nearly 4% of the customers migrated to the «Champions» segment. In value terms, this resulted in a 388% increase in referral value gains. This means that not only is the telecommunications firm increasing its revenue from all its customers, but that the customer base is growing, too. This allows the firm to greatly expand its customer base and find new revenue sources outside of just trying to cross-sell and up-sell to its current customers.

With respect to the «Advocates» segment, nearly 5% of the customers migrated to the «Champions» segment. This resulted in an increase of 61% in its average CLV. In this case, the telecommunications firm has been able to take customers who it would have initially ignored if they were looking only at CLV because of their low CLV and moved them toward the most desirable cell in the 2 × 2 matrix (those with high CLV and CRV).

It is therefore clear from these findings that the strategy was successful in not only migrating customers toward better cells, but also in moving these customers to cells that have significantly higher CLV, CRV, or both. Now, one might wonder how much it cost the company to run these campaigns, and whether the gains were worthwhile or not. The cost of the three campaigns, which included direct mail, email, and selected telephone calls for the 7821 customers (customers from the three cells: «Affluents», «Misers», and «Advocates») in the sample, was approximately $31,500. On a per customer basis, this would be nearly $4 per customer. The overall profit obtained through increases in each customer's CLV or CRV from each of the three campaigns was $486,090. Therefore, the overall ROI of the campaign was around 15.5.

As evident in Table 17.9, the ROI from running these three customized campaigns has generated significant gains in profit. It is also important to note that a considerable amount of customization is required to realize such gains. Therefore, while this study cannot be directly applied in another industry, with similar customizations similar gains can be achieved. Now that we have learned about CRV and its link to CLV, let us see the managerial implications of adopting this approach.

Table 17.9 Campaign results for «Misers», «Advocates» and «Affluents»

Segment	Total segment size (%)		% of customers migrated towards (%)			Average customer value before campaign		Average customer value increase after campaign		
	Before campaign	After campaign	Affluents	Champions	Advocates	1 year CLV	1 year CRV	Affluents	Champions	Advocates
Misers	21	9	4	4	4	$130	$64	CLV ↑ to $370	CLV ↑ to $310 CRV ↑ to $274	CLV ↑ to $334
Affluents	29	25	–	4	–	$1219	$49	–	CLV ↔ at $1219 CRV ↑ to $239	
Advocates	29	24	–	5	–	$180	$670	–	CLV ↑ to $290 CRV ↔ at $670	–

Source: Adapted from Kumar et al. (2007)

17.6.5 What Should the Focus Be on: Customer Referral Value or Customer Lifetime Value?

Companies like Bank of America and Vonage have introduced a value-oriented referral incentive program that rewards both the referral and the referring customer. Bank of America rewards both the referral and the referring customer $25 whenever a referral opens a personal checking account. Similarly, when a business owner opens a business checking account both the referral and the referring customer get $50.

On the other hand, Vonage leverages the social media buzz to reward the referring customer. For every referral that signs up for Vonage service, the referring customer gets 1 month of free service. Similarly, DIRECTV provides $100 to both the referral and the referring customer. This reward is offered in the form of $10 monthly bill credits for 10 consecutive months. These incentives seem to be in proportion to the typical value brought in by each member in the respective referral groups.

Therefore, it is clear that customers who score highly on the CLV measure are not the same customers who score highly on the CRV measure. Further, firms should measure both CLV and CRV to implement marketing campaigns that focus on customers based on both dimensions. A marketing campaign that focuses on both metrics will allow firms to both increase the profitability of each customer and, cash in on the power of positive WOM.

Now the question is how managers can know which campaign to choose—a campaign for CLV or a campaign for CRV? In other words, is there a trade-off when maximizing one versus the other? With information about the objective of the campaign, the stage of the product in its life cycle, the potential number of prospects in the pool, and the nature of competition in the market, managers can decide on the nature of the campaign that will drive revenue and profit.

A CLV campaign would be most appropriate in a situation where the goal is to get users to buy more in a specific category or buy across more categories. Typically, such campaigns happen in competitive markets where it is tough to acquire new customers or in niche markets where the prospect pool is very limited. On the other hand, a CRV campaign would be most appropriate in a situation where the aim is to acquire more customers/prospects through their current customers. This is because, the current customers may already be spending the majority of their budget with the company, and programs to increase cross-selling or up-selling would not yield much success. Of course, the caveat in selecting the choice of customers for CRV campaigns is to be cognizant of the fact that high-CLV customers are not the customers who refer the most. The study explained here shows the importance of measuring the value of a customer's own transactions *and* the value of their impact on the transactions of other customers, and not one or the other in isolation.

It is therefore important to encourage customers to build social networks and provide referral incentives for them to talk to other customers. Strong social networks can also be a source of long-term competitive advantage for both the customers and the firm. This is because, it becomes harder for the competitors to lure away customers who are tightly locked in to their social network, while at the same time consumers in a strong network enjoy ease of information sharing about products and services and the use of common products and services. Therefore, a firm should view its customers as skilled resources and work with them to build strong social networks through which both the firm and the customer can benefit.

Summary

Customer equity is the aggregation of the expected lifetime values of a firm's entire base of existing customers and the expected future value of newly acquired customers. The NPV objective function required to maximize the customer equity of a firm is related to the cash flow from each customer, the expected interpurchase time, and the cost and frequency of the marketing/communication strategies employed. The objective function is based on a probability model which predicts the interpurchase time of each customer, a panel data model which predicts the cash flows from each customer, and an optimization algorithm which maximizes the profits. By applying an optimization model,

a manager can know the extent to which he should use various contact channels. Cross analysis of duration of relationship and customer value obtained on the basis of the NPV maximization objective function indicates not all short-duration customers deliver lower profits, and not all long-duration customers deliver higher profits. Identifying and targeting responsive and profitable customers and deemphasizing efforts on some customers who were not profitable-irrespective of whether they are classified as long-duration or short-duration customers-would be a better approach. Customer value-based approach demonstrated its superiority to the duration of association approach in terms of profitable segmentation of customers.

Purchase sequence model captures the differences in the durations between purchases for different product categories. An individual customer-level profit function is developed to predict customer value. The success of the experiment based on the model demonstrated by higher revenue, lower cost of communication, lower number of attempts before a purchase is made, higher profits, and higher ROI for the test group, when compared to the control group, indicates the scope to which the customer value approach offers in improving the quality of marketing decisions.

The acquisition-process is an integral component of the research model. By linking acquisition and the retention process, it is possible to see a complete and unbiased picture of the drivers behind customers election/acquisition, relationship duration, and customer profitability. Also, making the necessary trade-off between offensive processes and defensive processes requires a full specification of the key dimensions of the customer-firm relationship. A more complete model specification addresses the key managerial question of whether the maximization of the respective objective functions as acquisition likelihood, lifetime duration, and customer value would lead to convergent or divergent resource allocation recommendations. This model applies mainly to situations where managers rely mostly on direct customer communication. Acquisition expenditures will have diminishing marginal associations with customer profitability. Retention expenditures will have diminishing marginal associations with relationship duration and with customer profitability. Highly interpersonal contact channels have a greater association with the likelihood of customer acquisition and relationship duration than less interpersonal contact channels. Though the results are specific to the empirical context, the model can be applied to any environment where acquisition and retention efforts can be separated. Managers can use the proposed integrated framework not only to better understand the drivers of profitability, but also to know how to maximize profitability through optimal allocation of resources.

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. The strategy described and illustrated here shows the effect of the customer intervention strategy in a telecom firm. Using the strategy, the firm realized a net revenue gain of $345,000 after accounting for the cost of intervention, and the ROI was close to 860%. This clearly shows that the key to retaining customers is to identify those who are likely to quit and reach them with appropriate messages.

Customer brand value refers to the differential effect of an individual's brand preference on his/her response to the marketing of a brand. When companies understand the link between CBV and CLV, they can efficiently allocate their resources to generate maximum value. The CBV is influenced by several factors such as brand knowledge, brand attitude, and brand behavior intentions. By establishing a link between these factors to the final customer behavior outcomes, firms can effectively manage the CBV and CLV simultaneously. Additionally, this linkage enables firms to take appropriate corrective measures to simultaneously build both the customer's brand value and lifetime value.

Customer referral value refers to a customer's expected future profits obtained through his referrals. This chapter has shown that it is important for firms to use both CLV and CRV metrics when managing customers. Customers who score high on the CLV metric do not score high on the CRV metric. Therefore, it is important to understand that a customer provides value to the firm either through CLV or CRV—or both. However, customers should be evaluated differently with respect to their total value to the company and then they should be approached with different types of marketing offers catering to maximizing CLV and/or CRV. This allows firms to increase the profitability of each customer and, in turn, increase the number of new customers buying products and services.

Exercise Questions

1. Consider a multiproduct company and discuss the likely sequence in which the average customer would buy these products. Why do you think an average customer may not be the best way to consider this problem?
2. Discuss the relative importance of the customer acquisition and retention processes from the perspective of customer lifetime value.
3. What are the important questions companies should think about in order to develop a successful proactive intervention strategy?
4. Should we invest in building brand value or customer value?
5. «By focusing referral program efforts only on the high value customers, it is possible for companies to increase their CRV. » Do you agree with this statement? If not, which customer segment(s) should managers focus on, and why?

References

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153–161.

Hogan, J. E., Lehmann, D. R., Merino, M., Srivastava, R. K., Thomas, J. S., & Verhoef, P. C. (2002). Linking customer assets to financial performance. *Journal of Service Research, 5*(1), 26–38.

Kumar, V., & George, M. *Saving customers through timely intervention*. Working Paper. Georgia State University, Atlanta.

Kumar, V., & Bhaskaran, V. (2010). *How influential are the influencers? Calculating word-of-mouth value of the networked individual*. Working Paper. Georgia State University.

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

Kumar, V., Petersen, J. A., & Leone, R. P. (2007). How valuable is word of mouth? *Harvard Business Review, 85*(10), 139–146.

Kumar, V., Venkatesan, R., & Reinartz, W. (2004). A purchase sequence analysis frame work for targeting products, customers and time period. Forthcoming in *Journal of Marketing*.

Reinartz, W., Thomas, J. S., & Kumar, V. (2005). Balancing acquisition and retention resources to maximize customer profitability. *Journal of Marketing, 69*(1), 63–79.

Rust, R. T., Lemon, K. N., & Narayandas, D. (2004). *Customer equity management*. Upper Saddle River, NJ: Pearson Education.

Rust, R. T., Zeithaml, V. A., & Lemon, K. N. (2000). *Driving customer equity: How customer lifetime value is reshaping corporate strategy*. New York: The Free Press.

Thomas, J. S. (2001). A methodology for linking customer acquisition to customer retention. *Journal of Marketing Research, 38*(2), 262–268.

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