Managing retailer profitability—one customer at a time!

V. Kumar*, Denish Shah, Rajkumar Venkatesan

ING Center for Financial Services, School of Business, University of Connecticut, Storrs, CT 06269-1041, USA

Abstract

This study examines how customer lifetime value (CLV) can be computed at individual customer level in a retail setting to maximize profitability. The study finds that maximum positive impact to CLV occurs when the customer cross-purchases, shows multi-channel shopping behavior, stays longer with the firm, buys specific product categories and purchases more frequently with the firm. Interestingly, the CLV follows an inverted U relationship with increase in return of prior purchases. Other interesting findings include a surprisingly low correlation between customer loyalty and future profitability and low correlation between stores’ historic revenues and future profitability. Several implications are suggested for retailers to manage and maximize customer profitability as well as store profitability.

© 2006 New York University. Published by Elsevier Inc. All rights reserved.

Keywords: Customer lifetime value; Customer profitability; Store profitability; Store management; Customer management

Introduction

When hurricane Frances was heading towards Florida, threatening a direct hit, trucks loaded with toaster pastries and six-packs were speeding down Interstate 95 towards Wal-Mart stores in the path of the storm. Through predictive analytics of its customer behavior, Wal-Mart knew that just before a storm, sale of products like strawberry Pop-Tarts increase seven-times their normal sales rate and beer is the top pre-hurricane selling item (Hays 2004). Interestingly, sale of goods such as flashlights and other storm relevant items paled in comparison. Such knowledge is not only power but also profits!

However, while the world’s largest retailer can boast of 500 terabytes of data stored on NCR mainframes, Wal-Mart’s data-farms are bereft of customer level information. In other words, while Wal-Mart can easily tell how many products it sold to its customers, it cannot tell which customer bought what product or which customer was more profitable and which customer was less profitable. Does this pose a problem for Wal-Mart? Not with its current dominant position in the marketplace with about 100 million customers (five-times the population of Australia) walking through its stores each week and generating about $30 million in net sales every hour. However, if the current trends in retailing are any indicator, Wal-Mart’s shift to individual customer management may seem inevitable. A recent study by KPMG conducted to analyze trends in retailing in 2005 in Germany found that ‘individuality in spite of volumes constituted the magic formula with which to enchant consumers’. Most importantly, the study advocates that ‘the future success of many retail companies will depend on how they can retain customers by means of individual propositions. Not surprisingly, retail firms have started thinking of various marketing initiatives that could be customized to individual customer-level. For example, Stop & Shop (a major grocery chain in USA) has recently introduced the concept of ‘Shopping Buddy’ in three of its locations in Massachusetts. The Shopping Buddy is a small tablet computer mounted on the shopping cart. Once activated, the Shopping Buddy displays personalized savings coupons and shopping history by aisle based on the location of a customer in the store, thereby offering a personalized shopping experience and promotions offer to every customer.

---

* Corresponding author. Tel.: +1 860 486 1086; fax: +1 860 486 8396.
E-mail addresses: vk@business.uconn.edu (V. Kumar), dshah@business.uconn.edu (D. Shah), rvenkatesan@business.uconn.edu (R. Venkatesan).

2 Wal-Mart’s 2004 net sales = $256 billion (source: Wal-Mart Stores, Inc.).
3 Source: http://www.stopandshop.com/.
More concrete evidence comes from a host of B-to-C companies in different industries that have reported a stellar financial performance in terms of profitability aided largely by superior management of their customers. These companies include Harrah’s Casinos (Bligh and Turk 2004), Continental Airlines (Hostmann 2005), TESCO (Child 2002), Royal Bank of Canada (Towergroup 2001), and Wyndham Hotels (Eardly 2003) to name a few. Each of these companies collects customer level information to unearth customer heterogeneity and subsequently deploys customer-specific marketing initiatives.

Not surprisingly, ‘customer management’ is becoming the mantra of virtually all business corporations. The traditional product-centric approach is fast collapsing to give way to the customer-centric way of thinking and doing business (Seybold 2001; Shah et al. 2006). Why is this change happening now? It is because advances in technology and database marketing in recent times are helping drive this change (Peppers and Rogers 1999; Winer 2001). Result—It is now relatively cheap and easy for retailers to collect and store customer level information, thereby creating a possibility to define and service customer segments of size one (Verhoef and Donkers 2001). From the retailer’s perspective, an immediate consequence of this phenomenon is to adopt ways and means to collect information at customer level and then develop suitable strategies and metrics to manage individual customer value. The most common method employed by retailers is through loyalty programs that serve as a mechanism to capture customer level information as well as a means to reward and hence retain the best customers. Such loyalty programs are typically set up to reward customers based on the amount they spend (for example, most credit card companies reward a point for every dollar spent), or the frequency of repeat buying (for example, newspapers and magazines give deep discounts to clients who advertise more frequently), or for the time spent with the company (for example, Sprint PCS gives a $150 handset rebate to customers that complete 18 months of contract).

The problem with this approach is two-fold:

1. They measure customer action in the past to induce future buying behavior (for example, rewarding a customer because he/she spent $x in the past).\(^4\)
2. They often prove to be poor predictors of future customer profitability (for example, a customer ‘x’ who has given greater revenue to the firm than customer ‘y’ need not mean that in the future, customer ‘x’ will contribute greater than customer ‘y’ towards the firm profitability) (Kumar and Reinartz 2006).

What should one do in such situations? The solution lies in applying a forward-looking metric that can compute the profitability of a customer in the foreseeable future (for example, the next 3 years). This is because past customer value is passe. What is more relevant to marketers is what marketing initiatives need to be administered today for a customer to provide value to the firm in the foreseeable future.

In the recent years, the customer lifetime value metric has generated a lot of interest in the research community. This is fueled by the fact that retailers nowadays have at their disposal customer level information collected from credit cards or the ubiquitous loyalty cards carried by almost all consumers in their wallets. This provides the retailer the means to deploy sophisticated tools to accurately model the future profitability for each customer, thereby providing a decision support system for the amount of dollars to be invested for each customer to sustain a profitable relationship. In fact, over time, the importance of CLV has evolved from merely being an important metric to a way of thinking and of doing business (Yu 2002).

So, what is the customer lifetime value (CLV) metric and how is it measured? In simple terms, CLV is defined as the net present value of future profits from a customer. Since the metric is forward looking, the dollar value associated with the CLV is an estimate or a prediction. Hence, it is imperative that the model used to measure CLV is specified properly.

In this paper, our endeavor is to first formulate a suitable model to compute CLV at individual customer level and then demonstrate how this metric can be implemented by a retailer to deploy various customer level and store level marketing strategies.

### Literature review

In relatively recent times, CLV has been a topic of considerable research. Most of the early research used CLV as a means to solve specific marketing decision problems pertaining to customer acquisition/retention decisions (for example, Blattberg and Deighton 1996; Wang and Splegel 1994). Determination or calculation of CLV was done mainly by considering specific numerical examples in particular business settings. Berger and Nasr (1998) were amongst the first to offer a systematic general approach to CLV computation by presenting a series of mathematical models that may be used in different instances. Over time, research importance and interest in the concept of lifetime value grew prompting more review papers such as Jain and Singh (2002) that summarized the findings and future directions of CLV-based research and Kumar et al. (2004) reviewed the various CLV approaches and best practice applications. While the review papers offered an excellent conceptual overview of CLV computation theory, some research has also been done to develop and calculate the CLV model using real-company data, thereby providing an empirical validation of the findings. For example, Verhoef and Donkers (2001) used data

---


\(^5\) Lately, there are few programs set up by retailers that reward future buying such as $20 rebate offered by Staples for future purchases of $200 or more. However, there is no empirical evidence in research literature to date that quantifies the benefits of such initiatives.
of an insurance service company in The Netherlands to calculate the potential value of a customer as the product of probability of a customer to purchase and the profit margin of that purchase. This approach works well in contractual settings where the expected purchase pattern of the customer is more or less stable. However, in non-contractual settings such as a typical retail store, customer purchase pattern could vary widely from customer to customer. In another contractual like setting example, Lewis (2005) described a dynamic programming-based approach to create optimal pricing aimed at maximizing the lifetime value of newspaper subscribers. Gupta and Lehmann (2003) showed a simple computational approach in terms of how one could use publicly available information such as a company’s financial documents to estimate the average lifetime value of a customer. Rust et al. (2004) showed that the change in a firm’s customer equity is the change in its current and future customers’ lifetime values, summed across all customers in the industry. The CLV was calculated as a function of frequency of category purchases, average quantity of purchase, and brand switching patterns combined with the firm’s contribution margin. The computed CLV was then averaged and applied across the potential customer population (about 44 million customers for American Airlines). Potential limitations with such an approach are as follows: (a) the model is inherently static, and (b) the model assumes that there is only one brand or product in the firm, and hence it could not consider cross-selling between firm’s brands or products. This poses practical limitations for adopting the model in a retail setting where retailers typically carry multiple brands and multiple product categories with cross-purchasing expected to be one of the most important drivers of customer value. Furthermore, the research of Gupta and Lehmann (2003) and Rust et al. (2004) assess the average value of a customer at some level of aggregation (or customer segmentation). In other words, these models do not provide individual customer level insights. This is imperative for the 21st century retailers that are armed with customer level information collected from customer membership (or loyalty) programs comprising of socio-demographic information as well as purchase transaction history and responses to various marketing initiatives.

There have been some studies relevant to the Customer Relationship Management (CRM) literature that deal with customer level analyses. For example, Reineartz and Kumar (2000) analyzed the relationship between the customer’s lifetime duration and profitability in the context of catalog and direct marketing industry. In a subsequent study, Reineartz and Kumar (2003) explored the antecedents of profitable lifetime duration of a customer. Knott et al. (2002) formulated and evaluated the next-product-to-buy models for improving the effectiveness of cross-selling at the individual customer level. Fader et al. (2005) proposed a simpler alternative to Pareto/NBD model in the form of a beta-geometric/NBD model for predicting customer’s future purchase contingent to past purchase behavior. While all of these studies discussed customer-level models, none of the studies computed the lifetime value of a customer.

Niraj et al. (2001) computed the lifetime value model for individual intermediary firms in the supply chain context. Venkatesan and Kumar (2004) offered a dynamic stochastic model to compute and maximize CLV using an optimal resource allocation framework for individual customers. Both of these studies are applicable and generalizable to B-to-B settings. In essence, these studies do not consider factors that may be of practical relevance to retailers in a typical B-to-C setting such as cross-channel shopping, customer demographics and linking store performance to customer value. In fact, there is no study to date that empirically validates the application of CLV metric at the individual customer level in a retail setting. The presence of this critical void in research is what has motivated the current study. The overall contribution of this article can be summarized in Fig. 1.

As shown in Fig. 1, we propose to fulfill the overall objective of maximizing retailer profitability through the proper application of the CLV metric. This entails specifying an appropriate model to compute the lifetime value at individual customer level and empirically proving (using real company data) that this forward looking view of customer profitability is more efficient than other traditional metrics in managing basic customer relationship programs such as customer loyalty programs. After evaluating the benefits of the CLV metric, we show how the CLV scores can be effectively applied by the retailer to maximize both customer and store profitability. For instance, by performing segmentation, profile and impact analyses in conjunction with the CLV score of the customers, retailers can uncover valuable customer-level insights thereby enabling them to deploy various customer management strategies (and tactics) as shown in Fig. 1. Similarly, CLV computation of customers by different stores can enable retailers to uncover some interesting and often counter-intuitive store-level insights leading to store management strategies (and tactics).

In essence, our study seeks to answer the following research questions for retailers:

1. What is the right metric to manage customer programs, for example, customer loyalty programs? Can CLV outperform traditional metrics?
2. How can the CLV concept be applied to measure and manage customer value?
3. How can the CLV concept be applied to manage store performance?

This article is organized as follows. We first evaluate the motivation of our paper in the light of the resource-based view theory and the abovementioned questions. Next, we perform an empirical cross-sectional time-series analyses using the database of a retailer. Based on the findings, we explore substantive tactical and strategic implications of our findings for practitioners to justify the contribution of our article as summarized in Fig. 1. Finally, we discuss the limitations and future directions of our study for researchers.
Theoretical motivation

The resource-based view (RBV) theory is regarded as one of the most influential frameworks in strategic management (Barney et al. 2001). According to the RBV theory, a firm can gain sustained competitive advantage from the resources and capabilities that a firm controls that are valuable, rare, and difficult to imitate (Barney 2001). Often, these resources and capabilities are firm-specific, non-tradable, and non-substitutable (Ma 2000); and can be viewed as comprising of tangible and/or intangible assets, including a firm’s management skills, its organizational processes, and the information and knowledge it controls (Barney 2001).

Srivastava et al. (2001) contend that marketing scholars have spent less attention towards extending the RBV theory as a frame of reference for advancing marketing theory or in analyzing core challenges in marketing practice. They suggest that further research is required to identify and document how particular market-based assets and capabilities lead towards creating and sustaining specific forms of customer value that eventually lead to superior performance.
In this study, we underscore the relevance of the RBV theory in the context of a retailing firm implementing the CLV metric. The adoption of CLV paradigm by a retailer would result in it owning a repository of customer level information offering deep customer insights and knowledge that would be unique to the firm. For example, based on a customer’s past transaction behavior with the firm, the retailer may be uniquely positioned to roll out specific cross-buy related marketing initiatives for that customer. Such an initiative may be impossible to imitate and/or fulfill by competing firms that lack the same level of customer information and/or product assortment.

Motivated by the RBV theory, our study proposes several CLV-based marketing initiatives for the retailer that serves to not only leverage its unique customer level insights but also build (tangible and intangible) resources that lead to sustained competitive advantage.

The following three questions serve as a precursor to help better appreciate the subsequent empirical analyses of CLV computation and implementation.

What is the right metric to manage customer loyalty?

The concept of customer loyalty has always been at the forefront of retailers’ quest to retain customers (Grewal et al. 2004). To identify loyal customers, retailers have typically analyzed customer behavior with respect to the following:

(a) For how long has the customer been active? (Reichheld 1996)
(b) How regularly does the customer buy? (Farley 1964; Massey et al. 1970)
(c) What is the RFM score of my customer? (Hughes 1996)

Based on these metrics, retailers often take future investment decisions for customer relationship management. For example, if a customer is deemed to be a long-life customer who transacted frequently with the firm in the past, then the retailer may allocate greater resources for that customer with the underlying expectation of increased profitability from that customer in the future. Intuitive as it may sound, a serious problem with this reasoning is that a backward-looking metric is employed to take a forward-looking decision. Further, some researchers in the past have cautioned against a weak relationship between behavioral loyalty (such as measures (a)–(c) above) and profitability (Dowling and Uncles 1997; Reinartz and Kumar 2002; Kumar and Shah 2004). Hence, it is worth exploring whether the traditional loyalty metrics should be treated as reliable indicators for furthering the relationship with a customer in future.

How can the CLV concept be applied to measure and manage customer value?

From the definition of CLV, we know that the lifetime value of a customer is the net present value of future profits from the customer. To arrive at the net present value, we need to deduct all future expenses expected to be incurred on the customer (such as marketing cost) from the expected future revenue to arrive at the net future value. This is then discounted to arrive at the net present value. The rate of discounting is usually the same as the cost of capital for the firm. It should be noted here that although we use the term customer ‘lifetime value’, the customer value is usually calculated for the foreseeable future depending on the type of industry. In the retailing industry, the prediction is usually done for the next 3 years.

Several approaches are available in the research literature to estimate the lifetime value of customers. However, given the nature of our data, we adapted the approach of Venkatesan and Kumar (2004) for computing CLV.

How can the CLV concept be applied to manage store performance?

Can the CLV metric help a retailer predict and manage store performance? The fact is that stores by themselves do not create wealth; customers do. Highly visible stores in prime locations are just one instrument among many to build the store’s brand equity. They can serve as the means to entice new customers and an anchor to hold existing customers. But stores can never be more important than the type of customers they reach when it comes to managing store profitability. This is important considering that retailers are often plagued by the store-management myopia, thus shifting their primary focus away from customer management. We discuss an interesting approach to store management using the CLV metric.

Modeling approach

Determining the correlation between loyalty and observed future profitability

We first evaluated customer loyalty as measured by: (a) relationship duration, (b) consistency of purchase frequency, and (c) RFM during the period 2001–2003. Next, we treated customer transactions in the year 2004 as the future period (with respect to the period 2001–2003) and called the customer profitability in this period as the observed future profitability (OFP).

The results from the two periods were used to computed the Pearson’s correlation coefficient between the customer’s

---

6 RFM score for a customer is derived from the simple or weighted combination of the customer’s recency, frequency and the monetary value of purchase.

7 It is the measure of regularity with which a customer makes purchases.
OFP (i.e., in year 2004) and customer loyalty (during the year 2001–2003) as measured by: (a) relationship duration, (b) consistency of purchase frequency, and (c) RFM. We compute the correlation coefficient between different time periods to see how well the historic measures (i.e., year 2001–2003) of loyalty help determine future customer profitability (i.e., in year 2004).

**Computing CLV**

We formulated the CLV model as summarized in Eq. (1).

\[
CLV_i = \frac{\sum_{t=1}^{T_i} GC_{i,t}}{(1 + r)^{\text{frequency}_i}} - \sum_{l=1}^{n} \sum_{m} c_{i,m,l} \frac{x_{i,m,l}}{(1 + r)^l} \tag{1}
\]

where \(CLV_{i,t}\) is the customer lifetime value for customer ‘i’; \(GC_{i,t}\), the gross contribution from customer i in purchase occasion r; \(c_{i,m,l}\), the unit marketing cost, for customer i in channel m in time period l; \(x_{i,m,l}\), the number of contacts to customer i in channel m in time period l; \(\text{frequency}_i\), 12/expint; expint, expected inter-purchase time for customer i; r, the discount rate for money; n, the number of years to forecast; \(T_i\), total number of purchases made by customer i; l, index for time in years; i, index for customer; t, index for time.

From Eq. (1), we can see that CLV consists of the following main components—(i) purchase frequency, (ii) contribution margin, and (iii) marketing cost. For accurate measurement of CLV, we must estimate the purchase frequency, contribution margin and marketing cost for each customer using suitable models and then combine the predictions from the three models to arrive at a single value representing the lifetime value of the customer in dollar terms.

(a) Modeling the purchase frequency for each customer

We modeled the purchase frequency of a customer using the generalized gamma model of inter-purchase timing developed by Allenby et al. (1999). The generalized gamma model also accommodates the commonly used exponential distribution for inter-purchase times (Reinartz and Kumar 2003). The likelihood function for the purchase frequency model is given by:

\[
L = \prod_{i=1}^{n} \prod_{j=1}^{J_i} \prod_{k=1}^{K} \Phi_{ijk} f(t_{ij}|\alpha_k, \lambda_{ik}, \gamma_k)^{s_{ijk}} S_{ijk} \times (t_{ij}|\alpha_k, \lambda_{ik}, \gamma_k)^{(1-c_{ijk})} \tag{2}
\]

where \(f(t_{ij}|\alpha, \lambda, \gamma)\) is the density function for the generalized gamma distribution (in other words, the probability of the jth purchase for customer i occurring at time period t, given \(\alpha, \lambda, \gamma\)); \(S(t_{ij}|\alpha, \lambda, \gamma)\) is the survival function for the generalized gamma distribution (in other words, the probability of the jth purchase for customer i occurring at a time period is greater than t, given that the jth purchase has not occurred until time t, given \(\alpha, \lambda, \gamma\)); \(c_{ij}\) 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; \(\Phi_{ijk}\) is the probability of observation j for the ith customer belonging to subgroup k. \(\alpha, \lambda, \gamma\) are the parameters of the generalized gamma distribution.

Given that we are using a generalized gamma distribution to model inter-purchase time and the likelihood function in Eq. (2), the expected time until next purchase is given by:

\[
\sum_{k} \Phi_{ik} \left\{ \frac{\Gamma(\alpha_k + \frac{1}{\gamma_k})}{\Gamma(\alpha_k)} \right\} \lambda_{ik} \tag{3}
\]

The ratio of 12 (because we use months as the unit of analysis) over the expected time until next purchase [which is obtained by modeling a generalized gamma distribution on the inter-purchase times as shown in Allenby et al. (1999)] gives the predicted purchase frequency as eventually used in Eq. (1). The parameters \(\alpha\) and \(\gamma\) establish the shape of the inter-purchase time distribution, and \(\lambda_i\) is the individual specific purchase rate parameter. The individual specific rate parameter, \(\lambda_{ik}\), in the generalized gamma distribution is assumed to be a random draw from an inverse generalized gamma (IGG) distribution. Specifically,

\[
\lambda_i \sim \text{IGG}(v, \theta, \gamma) = \frac{\gamma^v}{\Gamma(v)\theta^v} \lambda_i^{-(v+1)} e^{-(\frac{1}{\theta} \lambda_i)^v}
\]

where v and \(\theta\) are the shape and scale parameters of the IGG distribution, respectively, and \(\gamma\) is common to both the generalized gamma distribution (for the inter-purchase times) and the IGG distribution. Such a set up allows us to estimate individual specific purchase rate parameters even though there are only a few observations per customer.

The population is assumed to consist of \(k\) subgroups, and \(\Phi_{ik}\) provides the mass point (i.e., weight) for each subgroup. The probability of a customer belonging to each subgroup, \(\Phi_{ik}\), is modeled as a probit function of the antecedents and covariates of purchase frequency. Specifically we can represent the link function as, \(\Phi_{ijk} = f(x_{ij}\beta_i)\); where \(x_{ij}\) are the antecedents and covariates of purchase frequency for customer i in purchase occasion j, and \(\beta_i\) are the customer-specific response coefficients.

Our model framework, as represented in Eq. (3), resembles a Hierarchical Bayes formulation of the concomitant continuous mixture model. To address the issue of endogeneity we use the one period lagged value for all the antecedents and covariates used in our analysis (Villas-Boas and Winer 1999; Venkatesan and Kumar 2004).

---

8 Due to space limitation, we are constrained to provide full details. Readers are encouraged to refer to Allenby et al. (1999) for more information related to this modeling approach or contact the authors for more details.
In addition we also evaluated the performance of the proposed model framework with several alternative model formulations such as: (a) simple generalized gamma distribution model, (b) continuous mixture model, and (c) latent class mixture model to compare the performance with our proposed model. We found that our proposed model framework outperformed the alternative model specifications.

To account for any extraneous factors not accounted for by the antecedent and covariate set we propose to use the log of the lagged inter-purchase time. The specification of the model allows us to estimate individual customer level coefficients for the influence of the various covariates on the probability of a customer belonging to a particular subgroup, and hence the inter-purchase times.

(b) Modeling the contribution margin for each customer

The gross contribution for each customer was modeled using panel-data regression methodologies. Hence, the gross contribution model can be represented as:

\[ GC_{i,j} = \beta_0 + \sum_{k=1}^{n} \beta_k X_{i,j-1} + e_{i,j} \]  (4)

where \( GC_{i,j} \) is the gross contribution for customer \( i \) in purchase occasion \( 'j' \) measured in dollars; \( X_{i,j-1} \), the independent variable relevant to customer \( i \) in purchase occasion \( j-1 \); \( e_{i,j} \), the error term; \( n \), the number of independent variables; \( k \), the index for the independent variable; \( i \), the index for the customer; \( \beta_0, \beta_j \) are the coefficients.

We define gross contribution margin as the revenue the customer provides to the firm, whenever they make a purchase, minus the cost of goods sold. While the cost of goods sold does not change very much over time, there is a possibility of large variance in the revenue a customer provides over time.

Further, we tried various alternative functional forms for the gross contribution margin model, including: (a) using log-margin as a dependent variable, and (b) a polynomial specification for the lagged dependent variables to allow for non-linearity. We found that the simple linear specification of Eq. (4) provided the best in-sample fit and predictive accuracy.

To help select the appropriate customer-behavior-related independent variables that could be tested for predicting purchase frequency and/or the gross contribution of each customer, we referred to the previous research and theory as well as inputs from the business managers of the retailer. The variables tested and finally selected in the model are summarized in Table 1.

Any issues related to endogeneity were addressed by using lagged endogenous variables wherever necessary. The results were tested for multicollinearity using variance inflation factor and eigenvalues of the principal component analyses of the predictors.

(c) Computing the marketing cost for each customer

There are several methods available to compute the marketing cost for each customer. For example, it may be calculated as an aggregate measure by dividing the total marketing budget by the number of customers. A more sophisticated approach would entail calculating the total marketing cost separately for each customer based on the various marketing channels expected to be used to interact with that customer. This can be denoted as shown in Eq. (5).

\[ MC_i = \sum_{l=1}^{n} \frac{\sum_{m} c_{i,m,l} x_{i,m,l}}{(1 + r)^l}. \]  (5)

where \( MC_i \) is the total marketing cost for customer \( i \); \( c_{i,m,l} \), the unit marketing cost, for customer \( i \) in channel \( m \) in time period \( l \); \( x_{i,m,l} \), the incidence of marketing customer \( i \) in channel \( m \) in time period \( l \); \( m \), the marketing channels (for this retailer it was web and catalog); \( r \) is the the discount rate for money; \( l \), the index for time; \( n \), the number of years to forecast.

Eq. (5) provides the retailer the means to compute the marketing cost not only by individual customer but also by individual marketing channels adopted for the same customer. This is imperative given the fact that direct marketing cost could vary widely across customers and across communication channels. For example, it would cost a retailer a fraction of the cost to send three different shopping catalogs to a customer by electronic mail as compared to sending one glossy catalog by regular mail to another customer. Further, with the increasing trend of multi-channel marketing to the same customer, computing marketing cost as shown in Eq. (5) can help retailers accurately arrive at a fair estimate of the expected marketing cost per customer. The expected marketing cost is discounted by \( l \) years to arrive at the present value of marketing cost.

Since this study was specifically done with the objective of measuring and implementing the CLV metric for a retailer, we followed the directives specified by the retailer. According to the retailer, the best prediction of future marketing cost for each customer over the next 3 years could be taken as three-times the direct marketing cost in the most recent year (i.e., 2004). In other words, we assumed the direct marketing cost for each customer to be the same for the next 3 years. This is a naïve assumption. However, a quick look into the customer dataset did confirm the fact that historically the direct marketing cost per customer remained more or less constant for this retailer. Note that the marketing cost was available as the total marketing cost (across all channels) for each customer in the dataset.

The predictions from the three models (as explained in (a)–(c)) were integrated to calculate the CLV score for each customer as expressed by Eq. (1). The CLV scores were then used to rank-order all customers in descending
Cross-buying Number of different product categories a customer has purchased + n.a. Customers who purchase across several product categories have higher switching costs and recurrent needs (Bowman and Narayandas 2001; Reinartz and Kumar 2003).

Returns Number of products the customer returns on an average between two observed purchases ⊙ n.a. Returns provide an opportunity for firms to satisfy customers and ensure repeat purchases (Reinartz and Kumar 2003), but too many purchase returns can prove detrimental for the firm.

Purhcase of specific product category Indicator variables to indicate purchase of specific product category or item n.a. ± A customer’s purchase pattern may depend on the product category purchased (Reinartz and Kumar 2003). Contribution margin of the customer may be impacted depending on whether the product is a regular priced item or a deep discounted item.

Multi-channel shopping behavior Cumulative revenue from other channels (web and catalog purchase) n.a. + Customers are increasingly using different channels for shopping leading to greater customer profitability for the firm (Rangaswamy and Van Bruggen, 2005; Kumar and Venkatesan 2005).

Number of distinct channels used for transactions + n.a. 

Time elapsed between successive purchases Time duration between the current purchase and the most recent purchase - n.a. Customers who purchase very frequently or very occasionally are expected to spend less per purchase occasion as compared to customers who have a moderate level of time interval during successive purchases.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Operationalization</th>
<th>Expected effect on purchase frequency</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cross-buying</td>
<td>Number of different product categories a customer has purchased</td>
<td>+</td>
<td>Customers who purchase across several product categories have higher switching costs and recurrent needs (Bowman and Narayandas 2001; Reinartz and Kumar 2003).</td>
</tr>
<tr>
<td>Returns</td>
<td>Number of products the customer returns on an average between two observed purchases</td>
<td>⊙</td>
<td>Returns provide an opportunity for firms to satisfy customers and ensure repeat purchases (Reinartz and Kumar 2003), but too many purchase returns can prove detrimental for the firm.</td>
</tr>
<tr>
<td>Purchase of specific product category</td>
<td>Indicator variables to indicate purchase of specific product category or item</td>
<td>n.a.</td>
<td>A customer’s purchase pattern may depend on the product category purchased (Reinartz and Kumar 2003). Contribution margin of the customer may be impacted depending on whether the product is a regular priced item or a deep discounted item.</td>
</tr>
<tr>
<td>Multi-channel shopping behavior</td>
<td>Cumulative revenue from other channels (web and catalog purchase)</td>
<td>n.a.</td>
<td>Customers are increasingly using different channels for shopping leading to greater customer profitability for the firm (Rangaswamy and Van Bruggen, 2005; Kumar and Venkatesan 2005).</td>
</tr>
<tr>
<td>Time elapsed between successive purchases</td>
<td>Time duration between the current purchase and the most recent purchase</td>
<td>-</td>
<td>Customers who purchase very frequently or very occasionally are expected to spend less per purchase occasion as compared to customers who have a moderate level of time interval during successive purchases.</td>
</tr>
</tbody>
</table>

The logistic regression (Eq. (6)) method offered a simple procedure to estimate the coefficients by employing maximum likelihood. Since we wanted to create profile analyses for both high and low CLV segments, we ran two separate logistic regression models. In the first model, we set the dependent variable = 1 if customer belonged to high CLV segment, else 0. Similarly, in the second case, we set the dependent variable = 1 if customer belonged to low CLV segment, else 0. In each case, we regressed all DSLB variables available in the dataset due to the absence of any concrete research literature in the past to guide us in selecting the relevant DSLB variables for identifying high and low CLV customers.

### Evaluating store performance using the CLV metric

The retailer used in this study has a chain of 30 stores across USA with relatively larger concentration of stores on the east coast and west coast. Due to the presence of multiple stores, it was possible to find customers shopping from multiple stores of the retailer. For example, we can come across a customer who had historically made 80% of his/her purchases from Store A, 10% from Store B and 10% from Store C of the retailer. We used this information to assign customer value weights to each store. For example, Store A can be assigned 80% of value from customer 1 (who shops from Store A and some other stores/channels), 0% from Customer 2 (who does not shop from Store A at all) and 100% for customer 3 (who shops only from Store A), and so on. We repeated this procedure to distribute customer value weights for all stores.

Based on the distribution of average CLV across deciles, we divided the customer base into three segments: high, medium, and low CLV segments. Next, we used the drivers of CLV (i.e., relationship duration and the variables used to compute the contribution margin and purchase frequency as outlined in Table 1) to assess their impact on CLV for the high CLV segment of customers. Finally, we employed logistic regression as shown in Eq. (6) to evaluate which of the demographic, lifestyle and shopping-behavior (DLSB)-related variables available in the dataset varied significantly across the high and low CLV segments. Medium CLV segment was excluded from the analyses to maximize the difference in profile between a high CLV and a low CLV customer. Medium CLV segmentation was excluded from the analyses to maximize the difference in profile between a high CLV and a low CLV customer. In each case, we regressed all DSLB variables available in the dataset due to the absence of any concrete research literature in the past to guide us in selecting the relevant DSLB variables for identifying high and low CLV customers.
The lifetime value of a store was then calculated as the weighted sum of the net present value of the lifetime value of customers that shopped from that store minus the net present value of the rent for the store. In principle, this approach is analogous to the study of Gupta and Lehmann (2003) that computed the lifetime value of customers as a proxy for firm valuation. However, our CLV computation methodology is very different given the fact that we use a bottom-up approach—where the lifetime value is first computed at the lowest level (for each customer) and then aggregated as a weighted sum to arrive at the store value. Also, our analysis is based on the current set of customers and does not take into account new customers that may get acquired by the stores in future time periods.

After computing the store’s lifetime value, we assigned ranks to the stores based on past profitability (based on past revenues of the previous 3 years) and future profitability (based on net present value of customer profitability for the next 3 years). Each of the 30 stores was more or less of the same size and located in regions having similar demographics. Hence, we did not see a need to normalize the store’s profit potential for these factors. Finally, we computed the spearman’s correlation coefficient between the store’s past and future profitability ranks. Intuitively, one would expect a high correlation between the two rankings.

Data description

Customer data from a major retailer (name withheld due to confidentiality) selling apparels, shoes and accessories for both men and women are utilized for this study. Our sample set originally comprised of about 317,253 customers that made purchases from the company’s 30 retail stores in USA between 2001 and 2004. In this sample, we noticed that there were a small proportion of customers that were consistently very high or very low value purchasers. Since these customers had extreme observations with very low variance, we treated them as outliers and eliminated them from our analyses as they were needlessly skewing the sample’s distribution. The number of customers that were treated as outliers formed approximately 4% of the sample dataset. This resulted in a sample size of 303,431 customers that was appropriate for further analyses as shown in Fig. 2.

Next, the sample was divided into two cohorts of customers: Cohorts 1 and 2. Cohort 1 was defined as the ‘Model Building Sample’ and comprised of customers who had made at least one purchase prior to December 31, 2003. There were 242,745 customers in Cohort 1. Cohort 2 was defined as the ‘Model Validation Sample’ and comprised of customers who had made at least one purchase prior to December 31, 2004 and who were not included in Cohort 1. There were 60,686 customers in Cohort 2. We used Cohort 1 to calibrate the model and Cohort 2 to validate the calibrated model. The final model was used to compute the CLV for the entire sample set, i.e., 303,431 customers. Fig. 2 depicts the dataset in terms of number of customers and associated timelines used for data analyses and prediction.

Results and discussion of findings

Weak correlation between loyalty and observed future profitability

Our findings showed a weak correlation coefficient of less than 0.3 between OFP and consistency of purchase frequency and RFM. The correlation was the highest between OFP and relationship duration (0.37). The empirical results are summarized in Table 2.

Intuitively, one would expect a strong positive relationship between measures of customer loyalty and (future) profitability. That is, the more loyal a customer was in the past, the more profitable he/she should be with the firm in future. However, our findings seem counter-intuitive with a weak correlation coefficient between measures of loyalty and profitability. These results are consistent with the empirical findings of Reinartz and Kumar (2000) that found a weak relationship between loyalty and profitability for customers from four different industries—catalog, insurance brokerage, high technology and grocery.

The empirical results render strength to the argument that the retailer cannot afford to use the traditional loyalty metrics to manage customer relationship. This is because based on a traditional backward-looking metric, the retailer may end up investing time and resources to cultivate relationship with the wrong (or non-profitable) customer(s). To manage both loyalty and profitability simultaneously, the retailer needs to adopt a forward looking metric such as the customer lifetime value metric as the discerning metric to identify loyal customers who also show the promise of being profitable in future.

Gross contribution & frequency model results

The gross contribution model results are summarized in Table 3. This model provided a good model fit (R-square = 0.71) and the mean absolute deviation (MAD) was 65 for the estimation sample and 70 for the holdout sample. On comparison, the proposed model outperformed the

---

9 A naïve assumption here is that the customers’ purchase pattern across stores will remain the same in future time period.

10 The existence of a unit root in the gross contribution provided by a customer was rejected by the Dickey-Fuller Test.
Table 3
Gross contribution model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standardized coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged contribution margin</td>
<td>0.83*</td>
</tr>
<tr>
<td>Lagged cumulative revenue from other channels</td>
<td>0.76*</td>
</tr>
<tr>
<td>$ spent on product category A in previous purchase occasion</td>
<td>0.61**</td>
</tr>
<tr>
<td>Time elapsed since last purchase</td>
<td>0.11*</td>
</tr>
<tr>
<td>Square of time elapsed since last purchase</td>
<td>-0.08**</td>
</tr>
</tbody>
</table>

* Significant at $\alpha$ = 0.01 level.
** Significant at $\alpha$ = 0.05 level.

The log-linear model. In addition, we did not see any significant non-linear effects for any parameters in the data set.

Table 4 summarizes the results for the frequency model. The model had log marginal likelihood (LMD) of $3.4 \times 10^4$ and MAD = 2.4. Table 5 gives a comparison of the performance of our proposed frequency model and alternative competing models described in the earlier section.

As one can see from Table 5, our model provided a better log marginal likelihood (LMD) and forecasting performance than the competing models. In essence, the concomitant mixture framework appears to be better suited to model abrupt changes in the inter-purchase times, which is observed in our data.

Distribution of CLV scores

The average CLV for a top decile and a bottom decile customer was $1580 and $-152, respectively. The overall average CLV of a customer was $259. Fig. 3 shows the distribution of CLV scores across the 10 deciles.
Table 5
Comparison of proposed model with competing purchase frequency models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Our proposed model</th>
<th>Model A (simple model)</th>
<th>Model B (continuous mixture model)</th>
<th>Model C (latent class mixture model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log marginal likelihood (LMD)</td>
<td>$-3.4 \times 10^4$</td>
<td>$-4.7 \times 10^4$</td>
<td>$-4.1 \times 10^4$</td>
<td>$-3.9 \times 10^4$</td>
</tr>
<tr>
<td>MAD</td>
<td>2.4</td>
<td>4.2</td>
<td>3.5</td>
<td>3.1</td>
</tr>
</tbody>
</table>

The distribution of CLV scores across customers unearthed some fascinating insights for the retailer. First of all, most companies commonly believe in the Pareto Principle or the 80-20 rule. That is, the top 20 (or 30) % of the customers typically generate 80 (or 70) % of the revenue or profits (Zeithaml 2000). However, when we examined the customer-profitability distribution from the CLV perspective, we found that this retailer was actually losing money across 30% of its customers. The top 20% customers were actually accounting for 95% of profits! This is because there are several customers in the low CLV segment with negative CLV.

Given the CLV score distribution across customers, the question is—how and where can the retailer derive maximum customer profitability? The answer lay in uncovering the drivers of lifetime value for the retailer’s customers. To achieve this, we included relationship duration and variables from Table 1 (that were used to compute contribution margin and purchase frequency) as the drivers of CLV. The drivers of CLV are supposed to help managers develop strategies to increase the CLV of each customer. To demonstrate the effectiveness of such strategies, we measured the impact of changing the value of each driver of CLV for the high CLV customers. We increased the magnitude of each driver by 15% for this segment of customers and evaluated the corresponding expected increase in CLV for each customer. In practice, this can be achieved by the retailer through appropriate marketing interventions. For example, promote cross-purchase behavior by offering customized incentives to customers to purchase across different product categories. The results are shown in Fig. 4.

As the results indicate, even for the high CLV customers, the impact is significant.\(^{11}\) We varied the drivers by 15% as that was the extent of change most feasible from the retailer’s standpoint whose dataset was used. However, in general, the drivers could have been varied by other percentages (such as 5% or 10%) leading to a proportional change in impact (as the relationship is linear other than a small negative quadratic relationship for the amount of returns as shown in Fig. 5. This is consistent with the findings of Reinartz and Kumar (2003)). The simulation revealed some interesting insights for the retailer as discussed below.

**Impact of cross-purchase**

Cross-purchase is often cited as a critical success factor for retailers. For example, Wells Fargo Bank has articulated

---

\(^{11}\) We performed similar analyses for the medium and low CLV customers and found a higher lift in CLV (in percentage terms) as compared to the high CLV customers. In the interest of space, these results are not reported and discussed in this paper.
increase in cross-purchase as one of the top strategic initiatives for their business (Wells Fargo’s 2004 Annual Report). The online retailer Amazon regularly uses evidence of cross-purchase to boost further sales. For example, each time a customer purchases a single item from Amazon, he/she will get pro-active advice from Amazon to purchase additional relevant items based on the cross-purchase history of customers who had bought similar items.

From Fig. 4, controlling for other variables, a 15% increase in cross-purchase of customers in the top two deciles, can result in a 20% increase in their CLV. In other words, future customer profitability increases if the customer purchases more product categories from the retailer. Our findings render tremendous support to the core philosophy of relationship marketing that encourages building relationships and trust with the customers so that they are encouraged to purchase more from the firm, both in terms of value as well as number of product types.

Impact of multi-channel shopping

A 15% increase by customers in the top two deciles in spending from other channels (i.e., through web and catalog) can result in an 18% increase in their CLV. Hence, the results show that regular store customers, who also purchase from other alternative channels, contribute substantively towards increasing their lifetime value for the firm. This is an important finding in the light of the fact that customers are increasingly using different channels for shopping (Rangaswamy and Van Bruggen, 2005). Multi-channel shopping not only provides added convenience to shoppers (for example, 24/7 shopping over the Internet) but also serves to drive revenues for the firm by offering shoppers a greater variety of goods online or through the catalog which may not be feasible to carry physically in stores.

Impact of selling a specific product

Controlling for other variables, a 15% increase in spending by a customer in product category A from the top two deciles, can result in a 14% increase in their CLV. These findings can act as a bridge between product management and customer management. This is because the retailer can sometimes manage customer value by virtue of managing the sales of product A to customers.

Multi-product retailers often wonder which product(s) can impact the company’s bottom-line the most? An intuitive approach would be to look at the historic sales of all product lines. If Apple computers would have done similar analyses shortly after Ipod was launched, then Ipod may have never figured as the product to focus on. However, if the same analyses would have been done using CLV metric as the criterion, then Ipod purchase would have emerged as the most significant predictor of a high CLV customer for Apple. This is because Ipod served as a gateway for a new customer to get acquainted with Apple as a brand, download songs from Apple’s website ITunes (i.e., cross-purchase), and possibly explore more Apple products such as Apple’s Mac (Blakely 2004), all contributing to the future revenue from the customer. Similarly, for the retailer in our study there seems to be some causal relationship between purchase of product A and high CLV of the customer.

Impact of relationship duration

The contribution of relationship duration to the increase in CLV of the top two deciles customers is 12% when the relationship duration of a customer increases by 15% while controlling for other variables. Hence, it is important for the retailer to retain high value customers. This is consistent with the study of Dawkins and Reichheld (1990) who found that small shifts in customer retention rates can have a powerful impact on profits. According to their study, a 5-point gain in the rate at which a bank credit card company retains customers can yield a 75% increase in the value of a customer. However, our findings differ from this notion in the sense that the retailers should not try to retain all customers. In Fig. 3, the bottom 30% of the customers showed a negative CLV. Therefore, any marketing efforts to retain those customers may actually tantamount to a double whammy where the retailer not only loses money for retaining loss making customers but also for spending resources towards their retention. Hence, it is important for the retailer to realize that tenure is an important driver for CLV only when it is applied to a select set of customers as determined by future profitability potential. In other words, retailers should not try to retain all customers. Attrition of customers in the low CLV segment may actually improve the retailer’s overall profitability as a majority of customers in the low CLV segment are a burden for retailer’s marketing resources.

Impact of frequency of purchase

Controlling for other variables, a 15% increase in purchase frequency of customers in the top two deciles can result in a 7% increase in their CLV. This is an interesting result as what it tells us is that although purchase frequency is an important driver of CLV, it has the least positive impact on CLV as compared to other drivers such as cross-purchase and multi-channel shopping behavior for high CLV customers.

Impact of average amount of returns

Controlling for other variables, a 15% increase in return of goods purchased by customers in the top two deciles, results in a 2% decrease in their CLV. However, this relationship is negative quadratic in nature (as shown earlier in Fig. 5) following an inverted U relationship. The case in point is the fact that the return of goods can be a double-edged sword. It is imperative for the retailer to distinguish across customers making moderate to excessive returns on the basis of the CLV metric.

To summarize our findings: maximum positive impact to CLV occurs when the customer cross-purchases. Further, CLV is impacted positively if the customer uses additional channels other than the regular retail stores to make purchases, stays longer with the firm, purchases product category
A and makes more frequent purchases with the firm. The CLV follows an inverted U relationship with increase in return of prior purchases.

**CLV-based segments & profile analyses**

Based on the distribution of average CLV across deciles, we divided the customer base into three segments: high CLV (comprising of Deciles 1 and 2), medium CLV (comprising of Deciles 3, 4, and 5) and low CLV (comprising of Deciles 6, 7, 8, 9, and 10). As pointed out by one of the reviewers, this form of segmentation is sensitive to the CLV scores of individual customers and hence the relative size of segments can change over time if the CLV distribution changes. We recommend this form of dynamic segmentation to ensure sustained focus of customer management on customer value.

The profile analyses of the high CLV customers and low CLV customers resulted in some interesting group-level differences as illustrated in Fig. 6.

From the profile analyses, it was clear that the most profitable customers of the retailer were professionally employed and married females in the age group of 30–49 years with children, having high household income, and member of the store’s loyalty card. In addition, the high CLV customers stayed relatively closer to the store, and were multi-channel shoppers. In contrast, the low CLV customers were identified as relatively low-income, unmarried male customers in the age range of 24–44 years, who were primarily single-channel shoppers, not necessarily a store loyalty program member, stayed relatively farther away from the store and did not own a home.

It should be noted that most CLV models do not include demographics and product usage variables (Jain and Singh 2002). However, our methodology of combining the predictor variables with profile analyses overcomes the shortcomings of previous studies. Profile analyses of this nature can help the retailer put a ‘face’ to the CLV score of the customer. This is extremely useful when the retailer is acquiring new customers as discussed in the managerial implications section.

**The lifetime value of stores**

The lifetime values for the stores of the retailer are given in Table 6.

From Table 6, we can see that the rank-order of all 30 stores of the retailer based on the CLV differ substantively from the rank-order of the stores based on the historic store revenue and historic profits (Spearman’s correlation coefficient = 0.39, p < 0.05). We see a similar discrepancy when comparing the past and future revenue of a customer. The findings indicate that retailers cannot afford to rely on historic performance of their stores. Instead, they need to be sensitive of their customer portfolio and the future value of that customer portfolio. Since 30% of customers on an average result in negative lifetime value, stores need to exercise greater discretion in terms of whether they are acquiring and retaining the right customers. For profitable retention of a customer, the store manager can look up the CLV score of its current customers and use that as a decision support tool to prioritize direct marketing initiatives such as promotions and special discounts. For example, the store manager should not spend more than $176 (on an average) for a customer in
Table 6
Comparison of store performance based on revenue and profitability

<table>
<thead>
<tr>
<th>Store number</th>
<th>Store revenue ($ million)</th>
<th>Revenue rank</th>
<th>Store profitability based on the lifetime value of the store’s customers ($ million)</th>
<th>Profitability rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13.45</td>
<td>1</td>
<td>2.36</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>7.90</td>
<td>2</td>
<td>1.23</td>
<td>12</td>
</tr>
<tr>
<td>3</td>
<td>6.50</td>
<td>3</td>
<td>–3.21</td>
<td>29</td>
</tr>
<tr>
<td>4</td>
<td>5.79</td>
<td>4</td>
<td>5.46</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>4.32</td>
<td>5</td>
<td>1.84</td>
<td>6</td>
</tr>
<tr>
<td>6</td>
<td>4.20</td>
<td>6</td>
<td>–4.18</td>
<td>30</td>
</tr>
<tr>
<td>7</td>
<td>3.38</td>
<td>7</td>
<td>3.33</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>2.86</td>
<td>8</td>
<td>2.55</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>2.78</td>
<td>9</td>
<td>0.12</td>
<td>20</td>
</tr>
<tr>
<td>10</td>
<td>2.58</td>
<td>10</td>
<td>0.73</td>
<td>17</td>
</tr>
<tr>
<td>11</td>
<td>2.56</td>
<td>11</td>
<td>0.79</td>
<td>16</td>
</tr>
<tr>
<td>12</td>
<td>2.51</td>
<td>12</td>
<td>2.18</td>
<td>5</td>
</tr>
<tr>
<td>13</td>
<td>2.50</td>
<td>13</td>
<td>–0.26</td>
<td>22</td>
</tr>
<tr>
<td>14</td>
<td>1.90</td>
<td>14</td>
<td>1.45</td>
<td>10</td>
</tr>
<tr>
<td>15</td>
<td>1.88</td>
<td>15</td>
<td>–2.33</td>
<td>28</td>
</tr>
<tr>
<td>16</td>
<td>1.85</td>
<td>16</td>
<td>1.72</td>
<td>7</td>
</tr>
<tr>
<td>17</td>
<td>1.70</td>
<td>17</td>
<td>–0.27</td>
<td>23</td>
</tr>
<tr>
<td>18</td>
<td>1.69</td>
<td>18</td>
<td>1.62</td>
<td>8</td>
</tr>
<tr>
<td>19</td>
<td>1.52</td>
<td>19</td>
<td>1.00</td>
<td>15</td>
</tr>
<tr>
<td>20</td>
<td>1.33</td>
<td>20</td>
<td>1.29</td>
<td>11</td>
</tr>
<tr>
<td>21</td>
<td>1.24</td>
<td>21</td>
<td>1.58</td>
<td>9</td>
</tr>
<tr>
<td>22</td>
<td>0.99</td>
<td>22</td>
<td>1.05</td>
<td>13</td>
</tr>
<tr>
<td>23</td>
<td>0.98</td>
<td>23</td>
<td>0.56</td>
<td>18</td>
</tr>
<tr>
<td>24</td>
<td>0.98</td>
<td>24</td>
<td>1.01</td>
<td>14</td>
</tr>
<tr>
<td>25</td>
<td>0.92</td>
<td>25</td>
<td>–0.35</td>
<td>24</td>
</tr>
<tr>
<td>26</td>
<td>0.86</td>
<td>26</td>
<td>–1.10</td>
<td>27</td>
</tr>
<tr>
<td>27</td>
<td>0.72</td>
<td>27</td>
<td>0.31</td>
<td>19</td>
</tr>
<tr>
<td>28</td>
<td>0.64</td>
<td>28</td>
<td>–0.20</td>
<td>21</td>
</tr>
<tr>
<td>29</td>
<td>0.46</td>
<td>29</td>
<td>–0.80</td>
<td>25</td>
</tr>
<tr>
<td>30</td>
<td>0.27</td>
<td>30</td>
<td>–0.84</td>
<td>26</td>
</tr>
</tbody>
</table>

Decile 3 (see Fig. 3) to ensure profitable lifetime relationship with the customer.

In terms of acquiring the right customer, the store manager can look at the profile of prospective customers and prioritize customer acquisition resources in favor of customers whose profile is similar to a typical high CLV customer. Similarly, for a relatively new customer that has transacted only once with the retailer and hence does not have any transaction history, the store manager can look at the customer’s profile and estimate the future profitability based on the closeness of the customer’s profile with a typical high CLV customer (or a typical low CLV customer). Accordingly, the store manager may decide to extend (or not extend) customer retention promotion and hence try to cultivate (or not cultivate) a relationship with the customer in future. Also, rather than spending marketing resources on acquiring new customers, the store manager can look at the drivers of CLV and try to increase the value of its retained customers. For example, it may cost the retailer less to cross-sell to the (existing) right customers than to generate revenue through new customer acquisition.

Generalizing the results, an important finding of the study was the presence of low correlation between measures of loyalty used by the retailer in our study and future profitability of its customers. This could serve as a caveat for other retailers that may be correlating loyalty with past profitability of their customers. Further, the study helps identify and highlight drivers of CLV such as cross-buying, product returns, purchase of specific product category, multi-channel shopping behavior and relationship duration. These drivers are generic to any retailer. Based on these findings, other retailer firms can use the same drivers as a starting point to test the extent to which they influence the lifetime value of their customers as well as for assessing their stores’ future profitability (in case the retailer has a multi-store chain).

Managerial implications

Our findings hold important tactical and strategic implications for the retailers in general as listed below.

Paradigm shift in management

Frustrated with the failure of his company’s CRM program, a practitioner once defined CRM as Can’t Really Measure (Kellen 2002). While this may be part of the problem, a bigger problem with most CRM implementations is that they overemphasize the ‘relationship’ aspect with the customers. While customer relationships are critical for all firms, they are just the means to the firms’ overall goal of maximizing
customer profitability. The CLV metric facilitates a paradigm shift in doing business by taking the emphasis from managing customer relationships to managing customer value.

Customer value management

Our findings showed that as much as 30% of the customers of the retailer showed a negative lifetime value. Loss making customers is not an alien phenomenon. It is common for retailers to find a subset of customers that would be cherry pickers or a drain on the company’s resources by virtue of excessive return of goods purchased or utilization of customer service. The electronic retailer Best Buy identified such customers as ‘demons’ and undertook steps such as cutting back on promotions and charging restocking fees for returns to deter the ‘demons’ (Selden and Colvin 2003). The heterogeneity of potential customer value (a.k.a. CLV score) necessitates the need to identify and manage each customer (or customer segments) differently.

The greater the difference in individual CLV scores, the greater would be the need to obtain individual customer level insights to design marketing strategies unique to each customer so as to maximize the impact for each customer.

Loyalty management

Retailers commonly employ historic measures or backward looking metrics such as past customer spending or frequency of purchase as objective measures to manage customer loyalty. Our findings show that these measures often prove to have a poor correlation with the future profitability of the customer. Hence, it is imperative that retailers implement a forward looking metric such as the CLV metric before investing their valuable resources in loyalty management programs. The CLV metric ensures simultaneous management of loyalty and profitability of the customer.

Multi-channel shopping

There are strong evidences of a growing breed of multi-channel shoppers who prefer to use one channel (such as the web) for researching their product and then use another channel (such as the store) to make their purchase. These multi-channel shoppers tend to be more satisfied and loyal in the long run (Foresee Results/FGI Research Report 2005). Our findings showed that customers who shopped from other channels in addition to the primary shopping channel had a higher CLV score than customers who shopped from the retail store alone. This holds important implications for retailers who must consciously strive to develop a wider array of shopping and fulfillment options and take steps to ensure superior and consistent customer experience in each of the shopping/fulfillment channels. Further, retailers should design an integrated multi-channel marketing strategy to support the multi-channel shopping behavior of its customers.

Direct marketing

CLV provides a mechanism to prioritize and effectively target sales and promotion campaigns. For example, if a retailer is planning a clearance sale event then the retailer will be better off sending the clearance event flyer to low CLV customers rather than high CLV customers. This is because the probability of finding bargain hunters (or less profitable customers) will be much higher in the low CLV segment as compared to the high CLV segment. Similarly, the probability of finding loyal (and less price-sensitive) customers will be much higher in the high CLV segment as compared to the low CLV segment. Sending the clearance sale event flyer to high CLV customers could tantamount to cannibalization of the retailer’s business.

Up-sell & cross-sell

Sometimes retailers may find customers in their database having profile similar to high CLV customers but low CLV value. Such customers are ideal candidates for up-sell and/or cross-sell related marketing initiatives. Further, CLV analyses can be complemented with purchase sequence analyses (Kumar et al. 2006) to send the right promotion message to the right customer so as to maximize the potential of incremental profits from the customer. Most importantly, CLV metric enables retailers to be forward-looking, and hence pro-active in their marketing initiatives rather than backward-looking and reactive in their marketing strategies.

Optimal resource allocation

CLV gives the net present value of future profits from a customer, thereby providing the future attractiveness of a customer in dollar terms. Based on this information, retailers will have a reliable measure in terms of the amount of resources (in dollar terms) to allocate per customer. In other words, the CLV metric helps set a ceiling on the dollar value for investing resources to manage customer relations. In absence of such a forward-looking measure, retailers may run the risk of over-spending on a customer.

Acquiring new customers

Our study conducted a profile analyses for each customer. By looking at the profile analyses for high CLV customers, retailers can gauge what kind of new customers to selectively target and acquire in future to maximize the probability of profitability from the new customer. Alternatively, given the demographic profile of a prospective customer who has never transacted with the company, retailers can compare the prospective customer’s profile with a typical high or low CLV score.
customer and accordingly decide on the level of resources to be employed to acquire the prospective customer.

**Managing the store level marketing mix**

Traditionally, stores have always been managed through the traditional marketing-mix comprising of the 4 P’s of marketing. Linking CLV metric to store performance can offer store managers customer-centric drivers to increase store profitability. This will enable the marketer to apply the marketing mix variables in a more efficient manner (Blattberg 1998). For example:

**Pricing:** Pricing is increasingly evolving as a more sophisticated and strategic marketing-mix tool (Levy et al. 2004). For example, it has been empirically shown how retailers’ pricing strategy can be customized for different brands, categories, stores, chains, markets, customers and competitive situations (Shankar and Bolton 2004). Advances in pricing strategy literature aligned with the CLV paradigm can offer retail store managers rich insights with respect to issues such as: How price sensitive are the high, medium and low CLV customers? What is the risk of increasing the price for products that are typically purchased by medium CLV customers? Would lowering the price of products that are typically purchased by the retailer’s high CLV customers cannibalize the business?

**Promotion:** Pricing decisions have a bearing on the type of promotion. CLV analyses can help retailers address issues such as—What is the responsiveness of high, medium, and low CLV customers to different kinds of promotions such as special promotions and clearance sale? Do the high CLV customers respond better to in-store displays or through direct marketing?

Kopalle et al. (1999) showed that retailers should promote more frequently in future if customers are more price sensitive. However, since not all customers may be profitable in future, CLV analyses may help retailers decide whether steep price promotions such as clearance sales be only targeted (for example, through direct marketing) to the low CLV customers?

**Place or store location:** Store location is perhaps the most important consideration for a retailer when deciding to open a new store. Intuitively, prime locations that attract heavy people-traffic are often the obvious choices to open a new store. Not surprisingly, we found high revenues for stores in prime locations for the retailer in our study. However, when we calculated the profitability of the store, we saw a very different picture as astronomically high rent costs of prime locations were pushing down the profitability of the store. For example, a store in downtown San Francisco may succeed in attracting a lot of customers including tourists, but the relevant issue to consider for the retailer is whether the high rent premium for a store in prime location can attract not just large number of customers but large number of high CLV customers so that the store profitability is preserved over time. Hence, prior to opening a new store, the retailer should evaluate the typical profile of its high CLV customers (as done in our study) and then find a location that has a relatively high density of residents that match the profile of its high CLV customers.

**Product:** What kind of products do high medium and low CLV customers buy? What kind of product is more popular with the high CLV customers? Should the retailer launch/display more products of that type? How many products are typically purchased by a high CLV customer versus a low CLV customer?

**CLV implementation**

CLV implementation could present two major challenges—(a) availability of customer level information, (b) implementation given customer level information. Availability of customer level information is not a serious issue for most retailers today. With the advances in IT, reduction in storage cost and a plethora of loyalty card programs in the retail sector, most retail firms (such as grocery chains) have access to customer level information. The question then is how easy or difficult would it be to implement the CLV metric for a retailer. The relative ease of implementation generally depends on the organizational ability and commitment to manage change vis-à-vis its current practices. This is because CLV implementation enforces customer-centric marketing which could result in a major paradigm shift for traditional product-centric retailers. Nevertheless, irrespective of the cost or difficulty of CLV implementation, retail firms that have invested in individual customer value management in general have shown superior financial performance.

In the context of our study, the retailer firm used the CLV analysis as described in our paper to identify the bottom 10 stores (in terms of its CLV). Thereafter, using the CLV drivers as their decision criteria, the firm rolled out customized marketing initiatives (through direct marketing) to individual customers. For example, to promote cross-purchase, the firm offered customized incentives to customers that were historically making purchases in a specific purchase category to make purchases in a different purchase category. These initiatives resulted in about 42% increase in same store revenue for the bottom 10 stores in 1 year as compared to 20% overall growth of the retailer in the same period.

In summary—since it is the future profitability of a customer that will eventually drive the store performance, it is imperative for the retailer to manage store performance by looking closely at the current profile and the future profitability of the store’s customers.

**Limitations & future directions**

Some of the limitations of the study stem from the extent to which data was available for the analyses. For instance,
our model is based purely on the behavioral data of the customers. A better approach could have involved inclusion of attitudinal data along with behavioral data to arrive at a better prediction of future profitability of the customer. Next, the dataset did not include any competitor level information. Hence, it was not possible to model store substitution at the customer level. However, this was indirectly accounted for in the purchase behavior of the customer through the purchase frequency model. Finally, our lifetime value analyses is based on the current set of customers and does not attempt to speculate on the value of new customers that may be subsequently acquired by the retailer in future.

For the purpose of this study, we have adapted the CLV model from past research as the main objective of our study was to derive managerial wisdom relevant to maximizing retailer profitability as a consequence of implementing the CLV metric. However, there is tremendous opportunity for researchers to take this further by formulating a completely new and a more sophisticated model to compute CLV in a retail setting or improve the current model proposed in the paper. For example, there could be a relationship between gross contribution and frequency model which has not been explicitly modeled by the current framework.

The current study is based on a single retailer. It may be useful to repeat the study across different types of retailers so that the generalization of CLV drivers and managerial implications may be better appreciated.

An interesting strategy-based research question that emerges from this study is, should retailers always maximize every store’s performance? Sometimes, a chain retailer may use one store in a prime location to build brand awareness and traffic for its other stores, so the store itself may not make much money. We have not addressed this question in our study as the retailer in our study treated each store as an independent business unit when it came to financial accounting. (This is common in franchisee run retail business models as well.) However, this is worth exploring in future research using datasets of other retailers. Also, issues arise when customers shop from multiple stores of the same retail chain. In our model, we have tried to accommodate this possibility by dividing the CLV proportionally across multiple stores as determined from the past spending pattern of the customer. However, future spending pattern of a customer across multiple stores may not be the same as in the past (see footnote no. 9). Further, store-level purchases data may not be readily available. In such scenarios, it may be advisable to do the analyses at the retailer level rather than at the individual store level.

Multi-channel shopping is fast evolving as an exciting area for researchers. Our study indicated that customers who shopped through channels in addition to stores were more profitable. This can be extended further to quantify synergies between different shopping channels and evaluating the sequence of channel adoption. For example, how do high CLV and low CLV customers adopt different shopping channels; in what order? How can an integrated marketing plan be deployed across different channels to maximize the CLV?

Conclusion

There is an age-old marketing wisdom that dictates—“You can only improve what you can manage and you can only measure what you can manage”. Fast forward to the 21st century and we see retailers constantly seeking new methods to manage and improve their customer value. With the advances in technology (such as smart cards, RFIDs, etc.) and database marketing that further enable collection of customer level data, it is beyond doubt that customer value management is at the forefront of strategic thinking of most firms.

In such a scenario, the customer lifetime value metric will play a dominant role in enabling the retailers to accurately define, measure, and manage their customer value. However, customer lifetime value is not just a metric. As our study demonstrated, CLV can instill a new way of thinking and doing business that is both customer and profit-centric. Also, our study talks about possible extensions and implications of the CLV metric. We expect these extensions to grow with the increase in popularity and adoption of the CLV metric.

In the words of Blattberg and Deighton (1996)—“When the time is ripe to change direction, the signal usually comes from the environment, not from the organization. The winner is the company that reads the signal first”. Given the relative early stages of the adoption of the CLV metric, retailers that plunge forward with a full scale CLV-based business philosophy have the opportunity of leaving their competitors far behind in terms of developing a critical competitive advantage—‘better understanding and knowledge of their customers’.

Acknowledgements

The authors thank the editors, area editor, and the three reviewers for their valuable suggestions in revising this manuscript. We also thank the retailer firm for providing the data for the analyses. The authors are grateful to the participants of the University of Maryland marketing research camp, New York University marketing research camp and the executives of the Research Round Table for their comments on the earlier version of the manuscript.

References


