Aalto University
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Accuracy of Noncomplex Customer Lifetime Value Models in the Medical Service Context
The Case of a Telemedicine Service Provider

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ABSTRACT

Title
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Objectives
The accurate valuation of a customer relationship remains a challenge that researchers and companies alike are struggling to solve. The objective of this study was to assess the accuracy of noncomplex and deterministic customer lifetime value (CLV) assessment models in a semi-contractual service business context.

Methodology
The data set encompassed four years of longitudinal behavioral data from 150 customers of the case company. Six noncomplex CLV models were selected and used to (1) predict the CLV's of individual customers, (2) to sort the customers into four equally sized segments based on the rank order of their predicted CLV, and (3) to predict the combined CLV of the customer base. The predictive performance of the models was evaluated by comparing the predicted CLV's with the actual values calculated from a holdout sample.

Findings
Four models were found to be quite inaccurate and the remaining two models very inaccurate at predicting the CLV of individual customers. Four models were found to be somewhat accurate in sorting the customer base into four segments and more accurate in predicting the top 25% of customers. One model was also especially accurate in predicting the combined value of the customers and can thus be utilized in the business context of the case company for customer base valuation purposes.

Keywords
customer lifetime value, CLV, customer valuation, relationship marketing, customer segmentation

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1. Introduction

1.1 Background

The customer has commanded a central position in marketing for several decades (Dwyer 1989). Already in the beginning of the 1960's, Theodore Levitt called for placing customer creation and satisfaction first on the list of companies' priorities (Levitt 1960), and certainly ever since the so-called customer revolution of the 1980's, which led to the placement of the customer and the creation of customer value at the center of attention (Boyce 2000), managers and academics alike have been searching for an accurate way to calculate the monetary value of customers and more specifically customer relationships. Especially during the 1990's, customer-focused strategies, such as relationship marketing, started to gain foothold over the traditional marketing mix approaches (see for example Grönroos 1994). Since the time of establishment of the "customer at the center" paradigm, the focus has gradually shifted from creating customer value in general towards valuating the individual customers in accurate monetary terms (Boyce 2000).

According to Persson and Ryals (2014), another strong driver for the development of the interest in the accurate valuation of customers as assets has been the quest to convincingly demonstrate the effectiveness of marketing on company performance, i.e. the accountability of marketing (see for example Holm et al. 2012, Gupta et al. 2006 and Rust et al. 2004).

Also, the increasing importance of the service sector relative to the manufacturing sector, accompanied by the natural alteration of marketing practices into more relationship-oriented methods, made the accurate assessment of customer lifetime value more important than ever before (Hogan et al. 2002). Rust and Huang (2014) argue that the continuing rise in importance of IT and Big Data are fundamentally transforming, among other things, the whole marketing science by making it possible to provide increasingly personalized services to customers, thereby also necessitating a shift in the companies' focus from product profitability to customer relationship profitability, i.e. from transaction and product focus to relationship focus.

Many companies have started to utilize different customer relationship valuation methods and there are several models of varying complexity any company can choose from. The question is, how does one choose a valuation method that is the most suitable one for a particular situation and business context? Presently, a class of valuation models called customer lifetime value (CLV) assessment is often considered to be the most effective type of customer relationship valuation tools (see for example Ekinci et al. 2014 [1] and Rust et al. 2011) but, again, there are a large number of different lifetime value assessment methodologies available.

A widely used method for identifying the most suitable customer lifetime value assessment model is to consider in what type of a business context the models are most useful. A characteristic often considered crucial is whether a company operates in a contractual or a noncontractual relationship with its customers (see for example Venkatesan and Kumar 2004).

1.2 Objective of the study

The objective of this study is to assess the accuracy of relatively noncomplex customer lifetime value assessment methods that could best be utilized in a specific business setting, which will be explained next.

The American Telehealth Association defines Telemedicine, or Telehealth, as “the use of medical information exchanged from one site to another via electronic communications to improve a patient’s clinical health status” (American Telemedicine Association 2012).

The case company selected for this study shall be referred to as “Company X”. The company is a Finnish telemedicine services provider offering online consultation services for private and public healthcare facilities through its subsidiaries and partners. With its services the company helps its customers in the diagnosis of certain medical conditions, for example cardiac arrhythmias.

Company X provides a customer clinic with patient monitoring devices. The clinic transfers the monitoring data to Company X’s servers through a web service, after which the data will be analyzed by a specialist physician, who will make a full consultation report complete with treatment recommendations. The analysis report is then sent to the customer clinic, which is now better equipped to treat the monitored patient.

Currently the use of Company X’s services in the Finnish healthcare sector is very widespread and the company is in the process of implementing the service concept in several other countries. The focus area of this study covers those business operations of Company X, which take place in the Finnish market only.

The business context of Company X is contractual in the technical sense of the word: The company’s customers agree to three or four year contract periods with a yearly minimum volume, which will be invoiced at the end of each yearly interval during the contract period, even if the service is not used at all. However, the business context also has a noncontractual quality, since any use of the service beyond the quite low yearly minimum will be invoiced according to the number of times the service is used. Since the customers can control the amount of service they purchase, the business context of the case company can be characterized as “semi-contractual”.

When selecting an appropriate customer lifetime value model it is important to take into account the resources of the company and the complexity of the behavior of the company’s customers (Holm et al. 2012). Since the resources of Company X are somewhat limited and the behavior of the company’s customers is relatively noncomplex, the customer lifetime value assessment tools that Company X could reasonably be thought to utilize would most likely also be comparatively noncomplex and straightforward to implement.

1.3 Research questions

As mentioned before, the objective of this study is to assess and compare the accuracy of different, relatively noncomplex methods for calculating the lifetime value of customer relationships in the semi-contractual setting of Company X.

Hence, the main research question in this study is defined as follows:

How accurate are noncomplex Customer Lifetime Value models in a semi-contractual setting?

In order to comprehensively evaluate the accuracy of the CLV models, the following three supportive sub-questions were formulated:

1. How accurately do noncomplex CLV models predict the lifetime values of individual customers in a semi-contractual setting?

2. How effective are noncomplex CLV models at segmenting customers in a semi-contractual setting?

3. How accurately do noncomplex CLV models predict the lifetime value of the total customer base in a semi-contractual setting?

1.4 Structure of the study

After this introductory section, a literature review of the different concepts and models encompassing the concept of customer valuation will be presented in chapter 2, with special attention awarded to customer lifetime valuation models. Then, chapter 3 will describe the data, research design and methodology of this study, followed by a description of the results and their analysis in chapter 4. In chapter 5 the implications of the results of the study will be presented. Finally, chapter 6 will provide a description of the limitations of the study and will also highlight promising avenues for further research.

2. Literature review

2.1 Customer valuation in general

As the quest for calculating a precise monetary value for each customer relationship developed, there was an increase in interest towards formal customer accounting (CA) practices (Weir 2008). Guilding and McManus (2002) define customer accounting as "all accounting practices directed towards appraising profit, sales, or present value of earnings relating to a customer or group of customers". They identify five dimensions of Customer Accounting:

1. Customer Profitability Analysis (CPA)

2. Customer Profitability Analysis of customer segments

3. Customer Lifetime Value analysis (CLV)

4. The notion of valuating customer relationships as assets

5. The holistic notion of Customer Accounting (Guilding and McManus 2002).

An additional concept that can also be added into the same category of customer accounting or valuation is the concept of customer equity (CE) analysis.

Since the early days the focus has shifted away from the arguably less sophisticated and retrospective CPA analysis towards models that include also prospective analyses of customer relationships, i.e. customer lifetime value and customer equity assessment models. The customer lifetime value models typically aim to predict future profits generated by customers, whereas customer equity models involve calculating the sum total of all current and also potential CLV's of a company.

Weir (2008) characterizes CPA as the first stage of development in customer valuation techniques and defines CLV as a logical expansion of the CPA model into a more comprehensive model or tool. Additionally, Weir (2008) and Gupta et al. (2006) identify similarities between CLV as a marketing concept and concepts in the field of finance, for example the notion of a discounted cash flow.

Companies are usually looking for ways to maximize their profit. This can generally be achieved by using the firms' scarce resources in ways that maximize revenue coming from customers and minimize the costs associated with acquiring, serving and retaining the customers. In other words, firms strive to maximize the total value of their customer base (Zeithaml et al. 2001). But in order to achieve this objective of value maximization companies need to be able to make customer level marketing decisions, which in turn necessitate the accurate estimation of customer level value based on costs and revenues associated with each customer (Kumar et al. 2004).

It is generally accepted among researchers and companies alike that all customers are not equally valuable and in order to maximize profits firms should treat their customers differently (e.g. Zeithaml et al. 2001, Venkatesan and Kumar 2004, Homburg et al. 2008, Rust et al. 2011, Ekinci et al. 2014 [1]). Central to the idea of customer valuation is the notion that every individual customer relationship can be viewed as an asset of certain precise value or even as a liability to a company. As Jain and Singh (2002) point out, the loyalty of a customer, i.e. the continuing customer relationship, has value only when that customer is profitable. It seems clear that a company will not thrive with loyal but unprofitable customers and it seems equally reasonable to state that it will be better for a company to lose a low-value customer than a high-value one (Abbasimehr et al. 2013). Therefore, an integral part of the customer valuation practice is the differential treatment of customers of different monetary value (Boyce 2000).

Research has shown that strategies based on CLV calculations can increase total company profitability (see for example Rust et al. 2004, Kumar et al. 2008). Hence, revenue maximization and cost minimization can be achieved by first accurately estimating the value associated with each customer and then allocating marketing resources in a way that maximizes the total value of the entire customer pool.

The informal customer classification is widely known as the ‘‘80/20 rule’’, or the “Pareto law”, which states that in a typical company 80% of total profits, sales or value, depending on the version of the rule, can be attributed to only 20 % of a company’s customers (Ekinci et al. 2014 [1]). However, a two-tiered classification might not suffice and it is indeed quite common to categorize customers into more tiers; for example FedEx has successfully utilized a three tier system (Zeithaml et al. 2001) and a four tier system has also received support (see for example Storbacka 1997 and Zeithaml et al. 2001).

While it may be common sense that some customers are more valuable to businesses than others and should therefore receive preferential treatment, the emergence of a formal and comprehensive valuation of individual customers, and the allocation of marketing resources accordingly, only started to emerge in relatively recent times (See for example Boyce 2000). This can in part be attributed to the previous absence of proper tools such as specialized customer resource management (CRM) systems and also lack of workable models for calculating the lifetime value of customers.

While research has demonstrated the usefulness of CLV for profit maximization, Persson and Ryals (2014) find that at least in the context of leading Nordic retail banks the use of simple “rule of thumb” heuristics regularly override for example CLV calculations as a basis for managerial decision making.

Attention is now turned to a deeper analysis of customer profitability analysis, customer lifetime value and customer equity, with special emphasis awarded to customer lifetime value.

2.2 Customer profitability analysis

When the concept and applications of customer accounting began to gather interest it was first the customer profitability analysis that received the most attention (Helgesen 2007).

Customer profitability can be defined as “the difference between the revenues earned from and the costs associated with a customer relationship during a specified period” (Pfeifer et al. 2005). Generally, costs and revenues, and therefore profits, are not distributed evenly among customers (Zeithaml et al. 2001). While the revenues a company is receiving from customers might often be known quite well, the costs that each customer relationship generates and therefore the profitability of each customer or customer segment is usually much less clear (van Raaij et al. 2003).

Customer profitability analysis aims to generate useful information regarding the profitability of each customer, which is to be used in the optimization of the use of the company's scarce resources in such a way that makes the most financial sense. In practice, this often leads to ranking the customers according to their actual or potential profitability and dividing the customers into different tiers with for example different service levels (Lacey et al. 2007).

While the concept of prioritizing customers has sometimes been challenged because of potential negative effects, such as bottom level customers spreading negative word of mouth, or even because of ethical concerns (see for example Boyce 2000), it has been shown to pay off (see for example Homburg et al. 2008 and Kumar et al 2008).

The concept of ranking and prioritizing customers based on their profitability has been the topic of several research papers and it is quite widely recognized that firms should prioritize their customers (Homburg et al. 2008, Zeithaml et al. 2001). The underlying idea is that all customers are not equally profitable and some customers will never become as profitable as others. Hence, it is hard to justify the same level of customer service and marketing effort for all customers, and prospective customers.

According to van Raaij et al. (2003), the largest element in CPA analysis is the calculation of the costs of a customer relationship by using a method called activity-based costing (ABC), which will be defined in more detail in section 2.3.2.1. Van Raaij et al. (2003) present a six-step framework for conducting a customer profitability analysis:

First the active customers have to be identified. Van Raaij et al. (2003) define an active customer as one that has placed at least one order during the previous year but the definition naturally depends on the business context and objectives of the company. The next step is to investigate what activities are performed and to identify the drivers behind these costs. Then, data about all activities will be gathered and the profitability calculations will be performed. According to Weir (2008), the types of costs calculated and assigned to customers typically include for example discounts and commissions, delivery costs, inventory costs, technical support costs, costs of handling customer inquiries and customer service costs. At the fourth stage the results will be interpreted and scrutinized, and possible errors in the model and the calculations will be corrected. The fifth step in the model suggested by van Raaij et al. (2003) involves making use of the results of the CPA analysis to for example improve customer relationship management strategies. The sixth and final step is to establish infrastructure to enable the continuous use of CPA in the firm's daily processes.

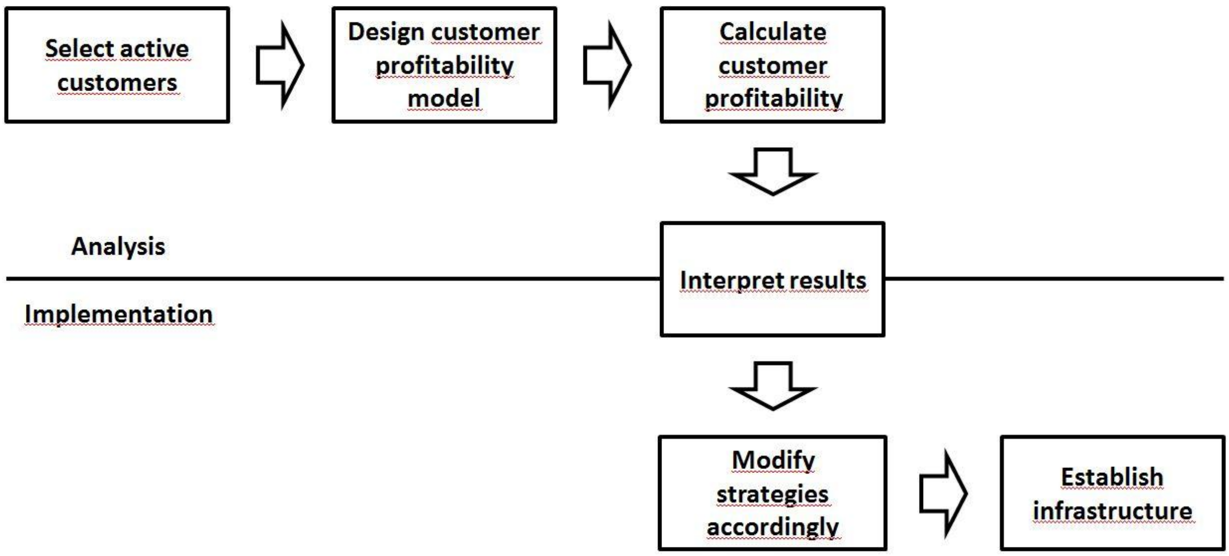

Figure 1 Customer profitability analysis, adapted from van Raaij et al. (2003)

An important limitation of customer profitability analysis is that it is retrospective, i.e. based on historical data on customer profitability, and thus ignores the future earnings that might become substantially larger than historical analysis leads one to believe (Rust et al. 2011). Therefore, the assessment of the value of a particular customer relationship should in general not be conducted by using only CPA.

2.3 Customer Lifetime Value

2.3.1 Customer Lifetime Value as a concept

In many situations merely calculating the current or retrospective value of a customer relationship using CPA will not offer adequate support for management decision making and planning for the future (Ekinci et al. 2014 [1]). In such cases better outcomes can be achieved by forecasting the full value of the customer relationship using a specific customer lifetime value model designed for that purpose.

As Rust et al. (2011) point out, a company can only act in order to have an effect on its future profits. Therefore decision making and planning should not be based on present or retrospective profit figures but instead on expected future profit figures acquired using prospective valuation models.

In 1974 Philip Kotler (1974) presented a customer lifetime value technique for estimating what he called “long-run customer profitability”, but it was not until the establishment of calculating the lifetime value of a relationship as a concept by Dwyer (1989) that it started to generate increasing interest (Persson and Ryals 2014).

Ryals (2008) broadly defines customer lifetime value as the forecasted net present value of a customer. Kumar et al. (2004) define CLV as the sum of cumulated cash flows of a particular customer over that customer’s entire lifetime, which are discounted using the weighted average cost of capital. More specifically, according to Venkatesan and Kumar (2004), CLV is typically calculated as a function of the forecasted contribution margin, the likelihood that the customer will continue in a relationship with the company, i.e. retention or churn rate, and the amount of marketing resources directed towards that customer. Dwyer (1989) defines lifetime value as “representing the present value of the expected benefits (e.g., gross margin) less the burdens (e.g., direct costs of servicing and communicating) from customers”. Blattberg et al. (2009) emphasize that the behaviors of the customer, firm, and competitor are subject to uncertainty, which makes true CLV a random, i.e. a stochastic, variable.

Inherent in the practical application of a CLV model is the use of a comprehensive CRM system. Direct marketers were the first to utilize database technologies in order to leverage customer information (Dwyer 1989). According to Verhoef and Donkers (2001), the use of customer information contained in databases makes it possible to channel investments towards those customers that are potentially valuable to the company and also to minimize investments directed towards non-valuable customers. Gupta et al. (2006) note that the increase in the volume of transactional customer data stored in databases makes it possible for companies to utilize data about actual customer preferences rather than only data about customer intentions.

Several studies indicate that allocating marketing resources to customers with a high forecasted CLV can lead to an increase in the value of a company's customer pool (see for example Venkatesan and Kumar 2004, Kumar et al 2008).

2.3.2 Elements of CLV

There are different approaches for measuring the lifetime value of a customer and the method by which they arrive at a certain customer value can vary considerably (Borle et al. 2008). The basic CLV models are generally deterministic, meaning that the input they require is determined qualitatively (Holm et al. 2012). Deterministic models are intrinsically unable to deal with randomness and the resulting potential problems with their predictive accuracy motivated researchers to develop quantitative statistical modeling techniques, which are able to deal with complicated customer relationship situations that cannot be solved algebraically (Kumar and George 2007, Pfeifer and Carraway 2000). In general, the complexity of the more sophisticated CLV models stems from the increasing complexity of the methods that are used to determine the inputs of the actual CLV calculation.

2.3.2.1 Basic model

In the basic CLV model the customer lifetime value is given by:

$$CLV = \sum_{i=1}^{n} \frac{R_i - C_i}{(1+\delta)^{i-0.5}}$$

where

i = the period of cash flow;

R_i = revenue from a customer in period i;

C_i = total cost of generating R_i in period i (fixed overhead costs are often not accounted for);

δ = discount rate; and

n = total lifetime of the customer expressed as the number of the time periods, which have been selected to be used in the calculation (Jain and Singh 2002). The 0.5 in the exponent of the divisor in the equation reflects the assumption that the cash flows occur in the middle of the purchase cycles (Berger and Nasr 1998).

As can be seen from the above equation, CLV is in general comprised of four basic elements (Blattberg et al. 2009):

1. Duration of the relationship
2. Revenue
3. Costs
4. A relevant discount rate

Duration of the relationship

Even though the term lifetime value suggests that the value of the entire customer relationship is taken into account, in practice the time horizon is usually three to five years, or even one year (Ekinci et al. 2014 [2]), although the duration of the relationship can also be set as infinite (Gupta et al. 2006).

Revenue

There are several ways of calculating the revenues that are inserted into the CLV formulas. The most straightforward method involves calculating the average revenue per customer for all time periods but since this approach excludes the possibility of the revenues increasing over time it might easily lead to unrealistic results (Blattberg et al. 2008, p. 130).

In the quest for adding realism to the calculations three elaborations of the naïve model have emerged:

1. Trend models, which consider the growth trend in the customer revenue data to account for the tendency of the revenues to increase over time.

2. Causal models, which use for example price and other appropriate variables to predict future spending by a customer.
3. Stochastic models of purchase rates and volume, which consider the historical purchase volume of a customer and mean purchase volume for the customer base to arrive at an estimate of future purchase volume (Blattberg et al. 2008, p. 130).

In the basic models the time periods are considered to be discrete and the customer in question is assumed to always spend a certain amount of money in each of the periods, for example the average spending in the customer segment (Borle et al. 2008).

Costs

The best practice for arriving at the cost figures to insert into the CLV models is generally considered to be the Activity-Based Costing approach. Searcy (2005) presents a five-step method for carrying out the analysis:

1. List all activities that result from servicing the customers (e.g. fulfilling an order)
2. Calculate the total direct cost of each activity on the company level.
3. Identify the products, services, and customers of the company.
4. Determine quantifiable cost drivers for each activity. A driver can be described as the customer action that causes the company to initiate the

listed activity (e.g. placing an order causes the fulfillment activity to take place).

5. Calculate the cost of each activity identified in step 2 on a disaggregate level, (e.g. cost of fulfilling one order or the cost of after-sales support).

An important issue regarding the computation of the costs of serving each customer is whether fixed overhead should be included and how it should be allocated to customers (Blattberg et al. 2008, p. 148). Often fixed overhead is not allocated because doing so could very easily lead to a negative customer lifetime value, even though the customer in question might be profitable and contribute to offsetting fixed costs (Blattberg et al. 2008, p. 149).

Discount rate

According to the Financial Accounting Standards Board (1985), the defining characteristic common to all assets is future economic benefit, which in a general business context leads to net cash flows for the company in question. Therefore in CLV literature the customer relationships are effectively considered as assets (Weir 2008, Pfeifer et al. 2005, Rust et al. 2004) and have to be evaluated as such. In the field of finance, the value of an asset is calculated as the net present value of all future revenues attributable to the asset in question, i.e. the value of all future cash flows has to be appropriately discounted (Pfeifer et al. 2005).

Discounting the value of future revenues involves accounting for the fact that because of the “time value of money”, i.e. the need to account for lost investment opportunities, inflation and risk, future cash flows are generally not considered as valuable as present revenues and therefore have to be discounted using a suitable discount rate (Arnold 2008, p. 50). The level of the chosen discount rate has a large effect on the managerial implications derived from any CLV model since a relatively high discount rate would translate into a relatively low value of the future cash flows (Blattberg et al 2008, p. 134).

When measuring the value of a customer relationship using CLV the relationship is essentially considered to be an equivalent to an investment project and the appropriate discount rate is in general determined to equal the opportunity cost of capital, i.e. the return that could be expected from an alternative investment project of similar risk (Blattberg et al. 2008, p. 134).

2.3.2.2 Extended basic model

Gupta et al. (2006) present a model that expands the previous model from Blattberg et al (2009):

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)r_i}{(1+\delta)^{i-0.5}} - AC$$

Their basic model is similar to the one presented by Blattberg et al. (2009) but two additional components have been added to the original four elements:

1. R_i - C_i is multiplied by r_i, which represents customer retention rate, or the probability of the customer repeat-buying, in period i.
2. Acquisition costs (AC) are deducted from the total.

Customer retention

Customer retention, i.e. the probability of the customer repeat-buying, or “being alive”, at a certain time period, is an important element in many CLV models (Gupta et al. 2006). The flip side of customer retention is customer churn or attrition, which can be defined at the propensity of a customer ceasing to do business with the company at a certain time (Neslin et al. 2006). Customer retention and churn probability have an effect on the expected length of a customer relationship, which in turn has an effect on the CLV of that customer (Neslin et al. 2006). Retaining existing customers is typically very beneficial for a company since over time existing customers tend to generate more revenue, spread positive word of mouth and become less costly to serve, thus becoming more profitable as the customer relationship develops (Berger and Nasr 1998).

In industries that are characterized by low switching costs, customer churn and the accurate identification of customer at risk of churning are of prime importance (Abbasimehr et al. 2013). Companies seek to mitigate the risk of customers churning by first predicting which customers have the highest risk of churning and then targeting them with marketing activities in order to increase the probability of retaining those customers (Neslin et al. 2006).

Acquisition costs

According to Ryals (2008) most CLV models do not take acquisition costs into account but the costs may be included in the case of a new or returning customer. The more common approach is to compare the acquisition cost and CLV measurement side by side in order to determine if an unprofitable customer, for whom the acquisition cost is larger than CLV, is unprofitable due to low CLV or high acquisition cost (Blattberg et al. 2008, p. 106).

2.3.3 CLV and marketing actions

A company initiates marketing actions in hopes of influencing affective customer responses, i.e. customer attitudes and satisfaction, and the behavior of customers (Blattberg et al. 2009, Gupta et al. 2006). The marketing actions can be directed towards three goals (Gupta et al. 2006):

1. Acquiring new customers and re-acquiring lapsed ones
2. Retaining existing customers
3. Developing existing customers, i.e. customer expansion

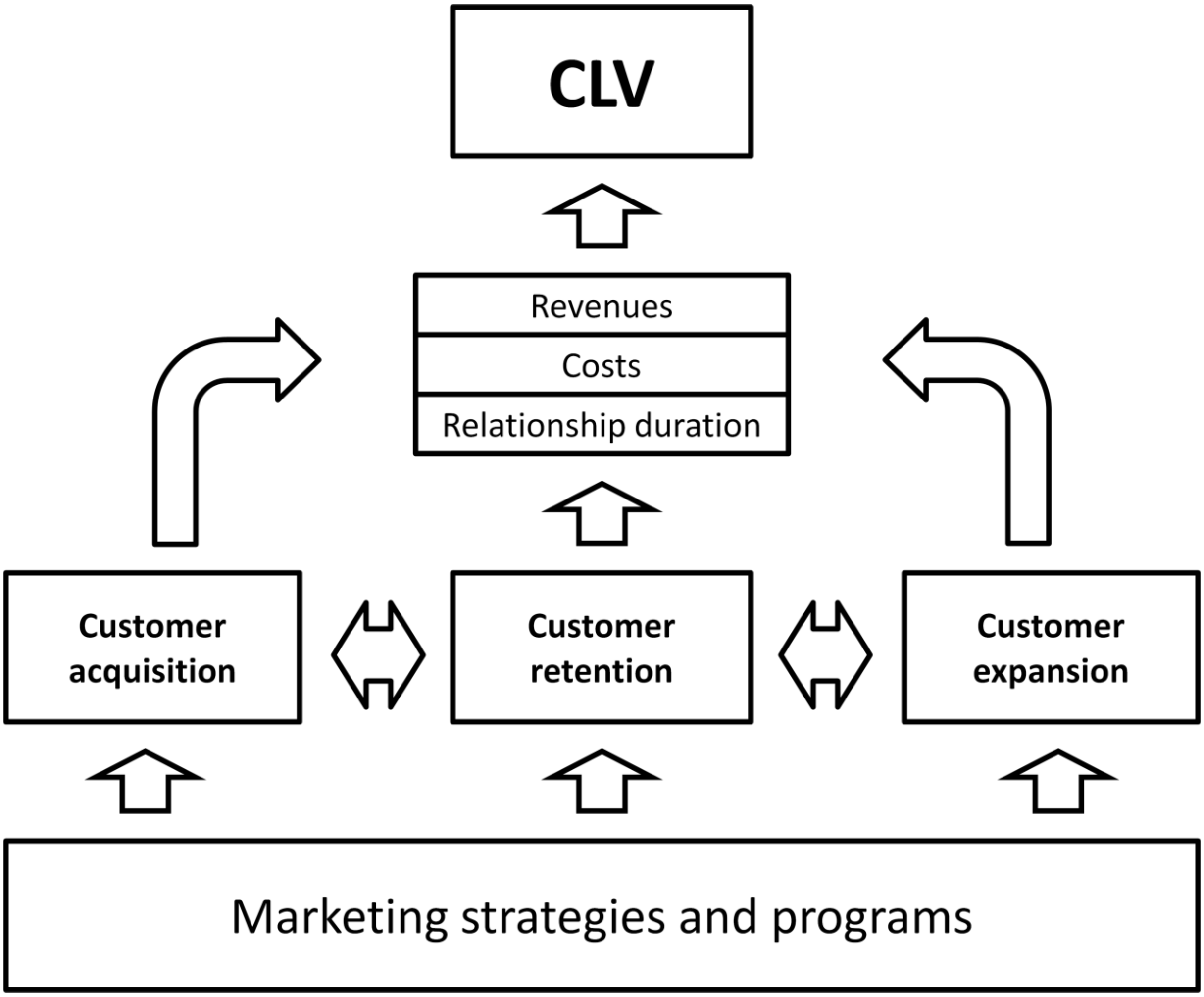

Figure 2 Framework for modeling Customer Lifetime Value, adapted from Gupta et al. (2006).

Marketing actions are designed to influence customer behavior, which in turn has an effect on the components of lifetime value (Gupta et al. 2006). As an example, the extent to which the sales staff utilizes customer lifetime value information in their customer interactions has been highlighted as an important factor in increasing the value of a company (Valenzuela et al. 2014) and several studies have demonstrated the possibilities of using strategies based on CLV to increase total company profitability (e.g. Rust et al. 2004, Kumar et al. 2008).

Homburg et al. (2009) define attempts to ensure that a customer relationship does not deteriorate or end completely, i.e. that the customer does not migrate to a lower value segment or churn, as defensive management of customer segment dynamics. Conversely, they define customer acquisition and customer development, i.e. customer expansion, as offensive management of customer segment dynamics.

2.3.4 Antecedents of CLV

Blattberg et al. (2009) find that customer satisfaction, cross/up-buying, multichannel buying and marketing are all positively associated with CLV, or rather with the different elements of CLV, but emphasize that the causality between the proposed antecedents and CLV is not clear, as for example high CLV can be the cause of an increase in marketing spending rather than the effect of an increase in marketing spending. Also, brand equity has been linked with customer acquisition, retention and profit margin (Stahl et al. 2012). Stahl et al. (2012) demonstrate the impact of the components of Young and Rubicam’s Brand Asset Valuator (BAV) construct of brand equity on the elements of CLV. The BAV measure consists of four aspects of brand equity:

1. Knowledge: Customer’s familiarity with the brand.
2. Relevance: How relevant to their needs the customers find the brand to be.

3. Esteem: How highly the customer regards the brand with regards to quality, leadership and reliability.
4. Differentiation: How different, unique or distinct the customer perceives the brand to be (Stahl et al. 2012).

Stahl et al. (2012) conclude that knowledge and differentiation aspects have statistically significant effects on all elements of CLV and that relevance and esteem have effects on at least one element of CLV.

If CLV is to be considered a meaningful marketing metric marketing actions must be shown to have an effect on CLV and indeed several studies have found an association between marketing activities and the duration of a customer relationship (Blattberg et al. 2009). Also, Reinartz et al. (2005) find that the amount of marketing expenditure and the way the marketing resources are invested have a positive effect on profitability.

2.3.5 CLV and customer equity

Weir (2008) considers the concept of customer equity (CE) to be the latest stage of development in the customer valuation paradigm. Customer equity can be defined as the sum of the discounted lifetime values of all of the firm’s current and potential customers (Rust et al. 2004).

In the fundamental Customer Equity equation, on which most CE models build, CE is given by:

$$CE(t) = N_t\alpha_t(AS_t - c_t) - N_tB_{a,t} + \sum_{k=1}^{\infty} N_t\alpha_t\left(\prod_{j=1}^{k}\rho_{j,t+k}\right) \cdot (RS_{t+k} - c_{t+k} - B_{r,t+k} - B_{AO,t+k})\left(\frac{1}{1-d}\right)^k$$

where

N_t = the number of new customers available for acquisition at time t;

α_t = the likelihood of acquisition at time t;

AS_t = acquisition sales at time t;

c_t = cost of goods sold at time t;

$B_{a,t}$ = investments into acquisition marketing at time t;

$\rho_{j,t+k}$ = retention rate at time t + k for customers acquired at time j;

RS_t = sales generated by retained customers at time t;

$B_{r,t}$ = investments in customer retention at time t;

$B_{AO,t}$ = investment in cross selling to retained customers at time t; and

d = a relevant discount rate (Kumar and George 2007).

The equation consists of three distinct parts.

The first part is:

$$N_t\alpha_t(AS_t - c_t) - N_tB_{a,t}$$

It represents the initial benefits obtained minus the acquisition costs from the acquisition of first time customers.

The second part is:

$$\sum_{k=1}^{\infty} N_t \alpha_t \left(\prod_{j=1}^{k} \rho_{j,t+k} \right)$$

This part deals with the customer retention probability.

The third part is:

$$\sum_{k=1}^{\infty} N_t \alpha_t \left(\prod_{j=1}^{k} \rho_{j,t+k} \right) \cdot \left(RS_{t+k} - c_{t+k} - B_{r,t+k} - B_{AO,t+k} \right) \left(\frac{1}{1-d} \right)^{k}$$

Here, customer retention is multiplied by the discounted retention profit (Blattberg et al. 2008, p. 497).

The fundamental equation of customer equity allows CE to be calculated as an aggregate measure for a customer segment (Kumar and George 2007).

In the customer equity model the management of the drivers of CE, namely customer value, brand and customer relationship, are combined to form a concept that can be utilized by companies to maximize their long-term success (Vogel et al. 2008). Advocates of CE propose that the marketing actions that a company initiates should be directed towards maximizing not only the CLV of individual customers but the combined CLV of the entire existing customer base and also potential future customers (Valenzuela et al. 2014). In the quest to make marketing accountable and to facilitate the justification of large marketing investments, several studies have found CE to be a good proxy for firm value (e.g. Silveira et al. 2012, Gupta et al. 2004) and, hence, a relevant measure for top management.

2.3.6 Categorization of CLV models

The bulk of the research on CLV calculations focuses on specific contexts because the customer data generated by companies in different industries and business contexts often differs in various important ways (Borle et al. 2008). Although categorization of CLV models can be challenging because of a model or the setting in which the model is meant to be used may possess characteristics of several, overlapping contexts, the literature review revealed four relatively clear categories that can be of assistance when comparing CLV models. The categories are:

1. Contractual vs. noncontractual
2. Lost-for-good vs. always-a-share
3. Deterministic vs. stochastic
4. Aggregate vs. disaggregate level

Next, the four categories will be explained in detail and a table categorizing different CLV models will be presented. A full categorization table can be found in appendix A.

2.3.6.1 Contractual vs. noncontractual contexts

Contractual context

Fader et al. (2005) define a contractual setting as one where the transaction opportunities are continuous and the time at which customers become inactive is observed. In a contractual context a longer customer lifetime duration is linked with higher customer lifetime value (Borle et al. 2008).

An important characteristic of a contractual setting is that the customer has to act to terminate the relationship with the company (Braun et al. 2011). Similarly, customers have to renew the contract with the company in order to keep using the company's services (Ascarza and Hardie 2013). Therefore the service usage and customer retention are interconnected processes.

In contractual settings it is important to accurately predict customer retention (Venkatesan and Kumar 2004).

Noncontractual context

Unlike in a contractual setting, where the end of a customer relationship is observed with certainty, in a noncontractual setting the company cannot determine the time of customer defection (Borle et al. 2008). Hence, a noncontractual setting is characterized by the need to infer the end of a customer relationship indirectly from customer behavior (Donkers et al. 2007).

In noncontractual settings managers will want to accurately predict the activity of a customer and the contribution margin of the customer (Venkatesan and Kumar 2004).

2.3.6.2 Lost-for-good vs. always-a-share

This classification can also be called the simple retention vs. migration dichotomy, where simple retention is synonymous with the lost-for good approach and migration is equal to the always-a-share approach. Both approaches are linked with retention, i.e. the likelihood that a customer will repeat-buy from the company during a time period, and the two approaches handle customer retention in ways that are quite different from one another (Gupta et al. 2006).

Lost-for-good

The lost-for-good models assume that customers always make purchases until they stop permanently, leave the company for good and cannot be re-acquired by the company (Rust et al. 2004). Essentially, they become equivalent to prospective customers who have never done any business with the company before and therefore have to be acquired in the same way as all other prospects. The customer retention probability, typically calculated from a segment retention rate, is usually set to less than one, i.e. the company considers the probability of a customer repeat-buying in the next period as less than 100 % (Rust et al. 2004). Therefore the retention probability of a customer will decline over time and customer attrition becomes more likely as time passes.

An example of a lost-for-good approach is the basic model presented by Gupta et al. (2006), where CLV is given by

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)r_i}{(1+\delta)^{i-0.5}} - AC$$

The formula includes a retention probability term r_i, which is the probability of the customer in question not having churned, at time i. The major limitation of this model and others like it arises from the retention probability term (Kumar and Shah 2015, p. 48). The nature of the term forces the lost-for-good models to view customer churn as a permanent phenomenon and prevents them from taking into account the possibility of a customer returning to do business with the company after a hiatus. Hence, the simple retention models tend to systematically understate customer CLV (Rust et al. 2004). Furthermore, the lost-for-good models ignore customer dynamics that go beyond simply being “alive” or permanently “dead” (Romero et al. 2013). Simple retention models have typically been applied in for example financial service and business-to-business settings (Blattberg et al. 2008, p. 109).

In lost-for-good contexts CLV is often modeled using various hazard models, Negative Binomial Distribution models or by utilizing machine learning algorithms (Gupta et al. 2006).

Always-a-share

Contrary to the lost-for-good approaches the always-a-share models assume that customers can allocate their spending across several companies, i.e. that customers might not allocate all of their spending on a particular product type or class to any one company (Rust et al. 2004). In the always-a-share approach so called migration models (see for example Dwyer 1989) are typically used, as these models can treat the customers as being “active” in spite of dormancy during one or several time periods as the retention probability can be adjusted accordingly (Rust et al. 2004). Therefore, the always-a-share model takes into account the possibility of a customer returning to do business with a company after a pause in purchases (Venkatesan and Kumar 2004).

When a customer returns from a hiatus and resumes business with a company the customer is considered to retain a memory about the existing relationship with the company and continue where they left off (Kumar et al. 2008). In the always-a-share approach a customer never permanently leaves a company. Generally, always-a-share models are considered more applicable for example for retail and catalog business contexts (Blattberg et al. 2008, p. 109).

A basic example of an always-a-share model on a disaggregate level is the following formula, where customer lifetime value is given by:

$$CLV = \sum_{i=1}^{T} \frac{CM_i}{(1+\delta)^{i/frequency}} - \sum_{l=1}^{n} \frac{\sum_m c_{m,l} \cdot x_{m,l}}{(1+\delta)^{l-1}}$$

where

CM_i = predicted future contribution margin from customer in purchase occasion i (for example in €);

δ = discount rate;

$c_{m,l}$ = unit marketing cost for the customer in channel m in time period l;

$x_{m,l}$ = number of contacts to the customer in channel m in time period l;

frequency = predicted purchase frequency for the customer;

n = number of time periods to forecast; and

T = predicted number of purchases made by the customer until the end of the time horizon (Venkatesan and Kumar 2004). In practice the purchase frequency of a customer can be estimated based on the customer's prior purchases (Venkatesan and Kumar 2004).

In always-a-share contexts CLV is often modeled and also optimized using Markov Decision Process techniques, i.e. stochastic dynamic programming models, Discrete-time Markov Chain models, or by using approaches based on Bayesian decision theory (Ekinci et al. 2014 [3]).

2.3.6.3 Deterministic vs. Stochastic

The early CLV models tended to feature only deterministic inputs, i.e. the inputs regarding customer behavior were entered directly into the formulas for calculating CLV (Holm et al 2012). In the deterministic models uncertainty is not explicitly taken into account (Blattberg et al. 2008, p. 540).

Deterministic models feature several limitations, which might hamper their usefulness for guiding resource allocation decisions, and therefore it is possible that more complex stochastic models offer distinct advantages over them (Holm et al 2012).

2.3.6.3 Aggregate vs. disaggregate

The early approaches for modeling CLV tended to measure the parameters on an aggregate level (e.g. Blattber and Deighton 1996, Berger and Nasr 1998). The aggregate approach involves measuring the model parameters as an average of a customer cohort, meaning that for example retention probability and marketing costs are investigated at a segment or even company level and then inserted into the CLV formula (Kumar and George 2007).

Since the early days the majority of later CLV models have moved to calculating lifetime value on a disaggregate level, i.e. on the level of individual customers (e.g. Venkatesan et al. 2007, Rust et al. 2011), which can be considered a more realistic and sophisticated approach (Holm et al. 2012).

Table 1 Categorization of CLV models*

Study	Context 1	Context 2	Measurement technique	Level of aggregation
Dwyer 1989	Noncontractual	Always-a-share	Stochastic	Company
Blattberg and Deighton 1996	Not applicaple	Lost-for-good	Deterministic	Company
Berger and Nasr 1998	Not applicaple	Both	Deterministic	Company
Pfeifer and Carraway 2000	Noncontractual	Always-a-share	Stochastic	Company
Rust et al. 2004	Noncontractual	Always-a-share	Stochastic	Individual
Fader et al. 2005	Noncontractual	Lost-for-good	Stochastic	Company and individual
Lewis 2005	Contractual	Always-a-share	Stochastic	Individual
Reinartz et al. 2005	Noncontractual	Lost-for-good	Stochastic	Individual
Haenlein et al. 2006	Noncontractual	Always-a-share	Stochastic	Individual
Kumar et al. 2006	Noncontractual	Always-a-share	Stochastic	Individual
Haenlein et al. 2007	Noncontractual	Always-a-share	Stochastic	Segment
Venkatesan et al. 2007	Noncontractual	Always-a-share	Stochastic	Individual
Borle et al. 2008	Contractual (membership)	Lost-for-good	Stochastic	Individual
Kumar et al. 2008	Noncontractual	Always-a-share	Stochastic	Individual
Ryals 2008	Contractual	Not applicable	Deterministic	Individual
Homburg et al. 2009	Noncontractual	Always-a-share	Stochastic	Segment
Jen et al. 2009	Noncontractual	Always-a-share	Stochastic	Individual
Kumar et al. 2010	Noncontractual	Always-a-share	Stochastic	Individual
Braun et al. 2011	Contractual	Lost-for-good	Stochastic	Individual
Schweidel et al. 2011	Contractual	Always-a-share	Stochastic	Individual
Rust et al. 2011	Noncontractual	Always-a-share	Stochastic	Individual
Ascarza and Hardie 2013	Contractual (membership)	Always-a-share	Stochastic	Individual
Romero et al. 2013	Noncontractual	Always-a-share	Stochastic	Individual
Schweidel and Knox 2013	Noncontractual	Always-a-share	Stochastic	Individual
Esteban-Bravo et al. 2014	Noncontractual	Always-a-share	Stochastic	Individual
Ekinci et al. 2014 [1]	Noncontractual	Always-a-share	Stochastic	Individual
Jahromi et al. 2014	Noncontractual	Always-a-share	Stochastic	Individual

*Please refer to Appendix A for a full description of the models in Table 1.

2.3.7 Limitations of CLV models

Most customer lifetime value models do not account for network effects, such as word of mouth, and instead treat the value of an individual customer as being independent of other customers (Gupta 2009). Yet, several studies show that for example the referral value of a customer can be significant (e.g. Kumar et al. 2007). Also, customers acquired through stimulated word of mouth using a customer referral program exhibit significantly higher contribution margins, retention rates and customer value (Schmitt et al. 2011).

Kumar et al. (2010 [1]) note that traditional measures of CLV overlook the possibility of a customer contributing to a company in ways that cannot be analyzed based on transaction data. Kumar et al. (2010 [1]) put forth the concept of Customer Engagement Value, which consists of four elements:

1. CLV (purchase behavior)
2. Customer referral value (more specifically the stimulated referral of new customers)
3. Customer influencer value (customer's ability to influence the behavior other customers and prospects)
4. Customer knowledge value (value of feedback from the customer)

Models that take referral value into account have been developed but are still the exception rather than the norm (see for example Kumar et al. 2010 [2] and Ryals 2008).

Another limitation of most CLV models is that they typically ignore competition simply because of lack of access to competitive data (Gupta et al. 2006). Most CRM databases do not account for transactions the company's customers perform with its competitors or the marketing efforts targeted towards the customers by the competitors (Rust et al. 2011).

Furthermore, Holm et al. (2012) point out that CLV models tend to assume that the service capacity of the company is fixed and cannot accommodate customers' possibly different future demands for service activities. A further assumption of many CLV models is that all customer relationships consume the same amount of customer service resources (Holm et al. 2012).

Also, most CRM databases do not feature data regarding customer attitudes, which is a further source of potential error in CLV calculations (Rust et al. 2011).

3. Methodology

3.1 CLV model selection

According to Holm et al. (2012) the sophistication and complexity of the CLV model to be utilized by a company should be decided by considering the degree of behavioral complexity that the company faces when servicing its customers. The level of customer behavioral complexity can be defined by considering the amount of variation in a company's customer base regarding three distinct areas:

1. Length of the customer relationships
2. Transaction frequencies and values
3. Cross-buying behavior, i.e. making purchases in more than one product categories (Holm et al. 2012).

The CEO of Company X characterized the customer behavioral complexity of the case company as being relatively low, scoring 13 out of a maximum of 30 on a Likert scale questionnaire adapted from Holm et al. (2012).

Table 2 Customer Behavioral Complexity of the case company

Answers on a scale from 1 to 5, from Strongly Disagree (1) to Strongly Agree (5)

1. Variation in relationship length

1.1 “In our markets customers switch between suppliers all the time.”

$\boxed{1}$ 2 3 4 5

1.2 “Some customers stay with our company for a long time while others prefer to shop around”

$\boxed{1}$ 2 3 4 5

2. Variation in relationship depth

2.1 “In our markets some customers perform only a couple of transactions per year while others trade all the time.”

1 2 3 4 $\boxed{5}$

2.2 “The variation in customer spending/use per transaction is large from transaction to transaction in our markets.”

$\boxed{1}$ 2 3 4 5

3. Variation in relationship breadth

3.1 “In our markets some customers buy from an extensive range of product categories while others buy from only one.”

1 $\boxed{2}$ 3 4 5

3.2 “The variation in cross-buying across categories is large in our markets.”

1 $\boxed{2}$ 3 4 5

Given the low customer behavioral complexity and the relatively small size of the company the use of a sophisticated CLV model could not be justified in the context of the case company. However, even though the adoption of a large-scale CLV system and strategy may not be justifiable, there are several models for calculating CLV that are relatively noncomplex and practical, and which can be utilized in the context of the case company with relative ease.

Noncomplexity in this context refers to models that are deterministic instead of stochastic and that are consequently less sophisticated and easier to implement (Holm et al. 2012, Calciu 2009). Compared with the more sophisticated models the noncomplex models, being more flexible and conceptually closer to managerial heuristics, are more appealing to managers and therefore have a higher chance of actually being used to support decision making (Calciu 2009).

Also, a study by Wübben and Wangenheim (2008) found that complex stochastic models did not lead to substantially better predictive accuracy over noncomplex heuristic models in a noncontractual setting and that in some areas the heuristics perform slightly better. Additionally, Donkers et al. (2007) have compared the performance of several models of varying degrees of complexity and sophistication in a contractual setting. They conclude that noncomplex retention models perform well, as long as cross-buying behavior responsible for customer expansion is taken into account. The added accuracy due to the inclusion of cross-buying stems from the growth in profits associated with it, a phenomenon which models that only account for retention are inherently unable to account for (Donkers et al. 2007). However, increase in profits over time can also be incorporated into the CLV calculations by constructing the CLV function in a way that reflects a realistic change in profits, which is in practice usually estimated using historical data (Berger and Nasr 1998).

The models selected for empirical application were:

1. Status quo model that assumes 100 % retention and does not take into account change in profit:

$$CLV = \sum_{i=1}^{n} \frac{R_i - C_i}{(1+\delta)^{i-0.5}}$$

2. Retention model that incorporates retention rate into the status quo model:

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)r_i}{(1+\delta)^{i-0.5}}$$

3. Trend model that incorporates individual change in profit into the status quo model:

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)(\Delta\pi)}{(1+\delta)^{i-0.5}}$$

4. Model that incorporates both retention rate and individual change in profit into the status quo model:

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)r_i(\Delta\pi)}{(1+\delta)^{i-0.5}}$$

5. Trend model that incorporates aggregate change in profit into the status quo model:

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)(\Delta\Pi)}{(1+\delta)^{i-0.5}}$$

6. Model that incorporates both retention rate and aggregate change in profit into the status quo model:

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)r_i(\Delta\Pi)}{(1+\delta)^{i-0.5}}$$

All of the selected models are noncomplex and deterministic variations of the basic CLV equation. In models 3 and 4 the term $\Delta\pi$ represents change in an individual customer's profit and the term $\Delta\Pi$ represents the aggregate change in profit. In all models the exponent of (1-δ) was set as i – 0.5, since the cash flows were assumed to take place in the middle of each time period.

3.2 Data

In this section an outline of the data used in this study will be presented. In order to protect the anonymity of the case company, revenue and cost data will not be described in detail.

3.2.1 Data sources and time horizon

The data set used in this study consists of four years of longitudinal behavioral data from 150 customers that were in a contractual relationship with Company X. The data encompass a timeframe extending from January 1st 2011 until December 31st 2014. Data from 2012 were used to calculate the forecasted CLV values for the customers until the end points of one and two-year time horizons. The last two years of the data set were used as a holdout sample to calculate the actual customer lifetime values.

Theoretically the lifetime value of a customer relationship should cover an infinite time horizon but in practice most companies calculate CLV for a finite lifetime (Donkers et al. 2007). The accuracy of CLV model results tends to diminish considerably when the time horizon is lengthened, which is why a shorter time horizon of one year can be considered a prerequisite for a realistic application of CLV models (Ekinci et al. 2014 [2]). Furthermore, the majority of companies tend to construct marketing plans using a one-year time horizon (Ekinci et al. 2014 [2]).

In this study data from 2012 was used to predict the individual CLV for each customer using both a one-year and a two-year time horizon.

3.2.1 Selection of customers

The sample set of customers was selected by first determining which users of the service had been active, i.e. had used the case company's services at least once during the first quarter of 2012. Then, all users that were considered test users and not yet customers at the end of the first quarter of 2012 were removed from the set of users. The remaining 150 service users were considered to be active customers of the case company and thus relevant for the purposes of this study.

3.2.2 Revenue data

The revenue of the case company consists of the specialist report fees and sales of consumables that are needed to perform the diagnostic tests. The consumables are priced very low since making profit on the consumables might jeopardize the company's exemption from VAT obligations, and also because their purpose is to support and expand the main source of revenue, i.e. the specialist consultation report fees.

3.2.3 Cost data

The cost data provided by the company included for example compensations to specialist doctors, medical device expenses, sales staff's commissions and hardware and software expenses that were considered directly related to delivering the core services of the company. The medical device expenses were calculated using a yearly depreciation rate of 25 %, which is in line with the accounting practices of the case company.

Other expenses included the cost of goods sold of service consumables, such as sensors and spare parts, and costs directly related to activities directed to or initiated by the customers, such as mailing packages, sending emails, making phone calls, attending sales meetings and repairing medical devices.

Fixed overhead expenses such as administrative and accounting expenses were not allocated to the customers in order to avoid the arbitrary assignment of costs that cannot be traced back to a particular customer in a meaningful way.

3.2.4 Retention rate

The contract period of three to four years is so long that the company has many large customers that are in the middle of their first or second period. Therefore for the purposes of this particular business context the retention rate was calculated from customer purchasing activity instead of being calculated from the percentage of customers that renew their contracts.

For the calculation of the yearly retention rate the number of active customers during the first quarter of 2011 was compared with the number of the same customers that were still active in the first quarter of 2012. An active customer was defined as a customer that was not a test user during the first quarter of 2011 and had used the services of the case company at least once during the three month timeframe. The definition of an active customer used in this study is consistent with the hiatus heuristic model used by Wübben and Wangenheim (2008) and the cutoff threshold of three months was deemed appropriate by the case company.

During the time period in question the churn rate was calculated to be 3,79 % and the valid yearly retention rate was thus equal to 96,21 %.

It is important to note that retention rate was assumed to be constant throughout the time horizon of the CLV forecast. Even though relaxing this assumption would perhaps lead to a more realistic modeling of CLV this would require the use of more sophisticated modeling techniques, which would not be appropriate, given the prerequisite that the models used should be noncomplex and deterministic (Blattberg et al. 2001, p. 134).

3.2.5 Change in profit

The yearly change in profit was calculated by comparing the profitability data from 2011 and 2012. The yearly change in profit during that timeframe was then assumed to continue linearly until the end of the forecasting horizons.

Models 3 and 4 make use of the profit development trends of each individual customer. Models 5 and 6 utilize an aggregate trend of the combined change in profit of the total customer base.

3.2.6 Discount rate

The discount rate was set to 10 %, which is in line with for example the discount rate used by Donkers et al. (2007). The discount rate was also deemed appropriate by the case company. Although the selection of a proper discount rate is an extremely important aspect in any application of a CLV model as a basis for managerial decision making, in the context of this study it is less significant, since the focus here was specifically on the effectiveness of the CLV models as forecasting tools.

3.3 Research design and methodology

Forecasted CLV's were compared with the actual CLV values calculated from the holdout sample using both one-year and two-year time horizons. The accuracy of the CLV predictions was evaluated using Mean Absolute Deviation (MAD) and Root Mean Squared Deviation (RMSD) calculated as a percentage of the arithmetic mean of average CLV (Donkers et al. 2007). MAD weighs all deviations equally, whereas RMSD amplifies the effect of larger deviations.

In addition, the accuracy of the CLV models was evaluated using a segmentation hit rate criterion similar to that of Donkers et al. (2007), where the customers were classified into four groups (top 25 %, upper middle 25 %, lower middle 25 % and bottom 25 %) based on the level of their actual and predicted CLV values. The effectiveness of the models was then evaluated by calculating the percentage of customers each model placed in the correct segment determined from the actual CLV values.

Finally, the predictive performance of the models was evaluated by first forecasting the total customer base value for one and two-year time horizons and then calculating the percentage deviation from the actual customer base values.

4. Results and analysis

In this section the results of the empirical application of the chosen CLV models will be presented and analyzed. First, the results of the performance test regarding the CLV levels will be presented and discussed, followed by the results of the performance test regarding the rank ordering of the customers into four equally sized segments. Finally, the performance of the CLV models with respect to predicting the total customer base value will be presented and analyzed.

4.1 Predictive performance with respect to CLV levels

The results regarding the predictive performance of the models with respect to CLV values are presented in table 3.

Table 3 Predictive performance, CLV values

	2013		2013 - 2014	
Model	MAD (%)	RMSD (%)	MAD (%)	RMSD (%)
1 Status quo	23.28	35.89	25.75	39.92
2 Retention	24.40	37.39	28.41	43.29
3 Change in individual profit	34.56	57.44	48.09	82.16
4 Retention + Change in individual profit	32.97	53.42	44.70	74.12
5 Aggregate change in profit	25.15	38.90	25.81	41.85
6 Retention + Aggregate change in profit	23.98	36.61	23.95	38.33

Values presented as % of average actual CLV

As can be seen from table 3, none of the models can be said to predict CLV levels especially well and models 3 and 4 performed particularly poorly. Since both models use individual growth trends it seems that the yearly change in profit of individual customers is too erratic for it to be utilized as a basis for trend estimation in the simplified manner used in this study.

The Status quo model performed the best when a time horizon of one year was used, with a mean absolute deviation of 23.28 % and a root squared mean deviation of 35.89. However, when the time horizon was extended to two years the Retention + Aggregate change in profit model (model 6) was the most accurate model in predicting CLV levels. Since the Status quo model in no way takes into account changes in customer profit or the possibility of the customer churning, it is reasonable to expect the model's margin of error to increase significantly as the number of periods in the time horizon increases. Additionally, it seems equally reasonable to postulate that a CLV model capable of accommodating a realistic change in profit and retention based on historical development figures of the customer base might achieve an advantage over the Status quo model when longer time horizons are used.

4.2 Predictive performance with respect to customer segmentation

The results regarding the predictive performance of the models with respect to customer segmentation are presented in table 4.

Table 4 Predictive performance, segmentation hit rate

	2013	2013 - 2014
Model	Hit rate (%)	Hit rate (%)
1 Status quo	70.67	71.33
2 Retention	70.67	71.33
3 Change in individual profit	64.00	59.33
4 Retention + Change in individual profit	64.00	59.33
5 Aggregate change in profit	70.67	71.33
6 Retention + Aggregate change in profit	70.67	71.33

Values presented as % of correctly segmented customers

The models 1, 2, 5 and 6 all performed equally well, or poorly, in segmenting the customers into four categories based on their CLV rank order. Models 3 and 4 performed worse than the other four models. The four more successful models correctly segmented slightly over 70 % of the customers. Interestingly, for models 1, 2, 5 and 6 the hit rates for CLV predictions spanning the two-year time horizon were higher than those calculated using a time horizon of only one year.

As mentioned before, a factor explaining the relatively poor performance of models 3 and 4 is the use of an individually calculated change in profit instead of the aggregate trend. The change in profit of individual customers was quite erratic, which makes the extrapolation of individual change in profit more error-prone than the aggregate trending, since in the aggregate change the individual errors cancel each other out to some extent.

Even though the models were not very successful at ordering the customer pool into four segments, they did predict the top 25 % substantially better. The hit rate of models 1, 2, 5 and 6 for the top segment was 86.49 % for a time horizon of one year and 81.08 % for the two-year horizon. Additionally, the models predicted the bottom 25 % of customers somewhat more accurately than all four segments combined. The added accuracy regarding top and bottom segments has a natural explanation; one would expect to have a worse hit rate in the middle segments than in the top and bottom segments, since whereas a customer in either of the middle segments can be misclassified into both higher and lower segments, a customer in the top or bottom segment can only be misclassified in one direction, thereby making misclassification less likely. Additionally, the CLV range was largest in the top segment, which means that a customer in the top segment will tolerate a larger relative error in predicted CLV without being misclassified than customers in the other segments.

4.3 Predictive performance with respect to total customer base valuation

The results regarding the predictive performance of the models with respect to total customer base valuation are presented in table 5.

Table 5 Predictive performance, total customer base valuation		
	2013	2013 - 2014
Model	Deviation (%)	Deviation (%)
1 Status quo	- 6.54	-13.15
2 Retention	-10.08	-17.94
3 Change in individual profit	13.56	21.37
4 Retention + Change in individual profit	9.26	14.36
5 Aggregate change in profit	8.59	8.69
6 Retention + Aggregate change in profit	4.48	2.54
Values presented as % deviation of actual total customer base value		

From table 5 it can be seen that model 6 was clearly the most accurate one in total customer base valuation in both time horizons. Regarding the time horizon of one year, the second most accurate model was model 1. Regarding the two-year time horizon, the second most accurate model was model 5.

Models 1 and 2 underestimated the combined value of the customers. This result is as expected; if the aggregate change in profit is positive, as it was in the case of Company X, model 1 and model 2 will often underestimate aggregate CLV, since they do not take change in profit into account. Additionally, model 2 assumes that a portion of the customers will churn every year. Conversely, models 3, 4, 5 and 6 overestimated the combined CLV of the customer base.

Model 6 slightly miscalculates the combined CLV of customers but it was nevertheless very accurate compared to all other models. By taking into account aggregate retention and aggregate change in profitability, and assuming both remain constant model 6 was able to estimate the value of the customer base very effectively. Additionally, model 6 was able to predict the value of the customer base more accurately in the case of the longer time horizon.

5. Discussion

This study compared the predictive performance of six noncomplex, deterministic CLV models. All of the selected models performed quite poorly with respect to predicting CLV levels of individual customers and segmenting the customers using a ranking method. However, four models out of the total of six were able to predict the top 25 % of customers with reasonable accuracy and could thus conceivably be used to identify the most promising customers in order to for example target them with preferential service. Nevertheless, the results indicate that the models do not fit the business context of the case company very well when the objective is to predict individual CLV values or to segment the customers.

When it comes to the valuation of the combined customer base, the model accounting for aggregate retention and aggregate change in profit (model 6) performed very well with a deviation of 4.48 % when a time horizon of 1 year is used and only 2.54 % in the case of a time horizon of two years. Hence, it can be stated that model 6 fits the business context of Company X well and can be considered a viable option when selecting a method for estimating the combined value of existing customer relationships, especially since the model is relatively noncomplex and straightforward to implement. However, it should be emphasized that for company valuation purposes it would be more appropriate to use a customer equity model, which would take into account also the value of potential future customers.

It can be concluded that model number 6 is the most accurate model out of the ones selected for this study. It is the most accurate model in all but one area; the Status quo model (model 1) predicted the CLV's of individual customers slightly more accurately than model 6 when a one-year time horizon was used.

Both the predicted and actual CLV values that can be obtained using the methods presented in this study are of course very dependent on the factors that are considered relevant and are consequently accounted for in the CLV calculations. Therefore, any company wishing to calculate the value of their customer relationships will have to consider their particular needs and objectives when deciding what CLV model to use and what factors to take into account.

6. Limitations and future research opportunities

There are several limitations that should be taken into account when considering the results and implications of this study. The results of the study are context-dependent and cannot be generalized without further practical application of the models in other business contexts.

The objective of this study was to investigate the performance of noncomplex, deterministic CLV models in a specific business context. It can naturally be hypothesized that adding sophistication to the CLV model could lead to better predictive performance in estimating CLV. Therefore, further studies that apply for example stochastic CLV models in a similar business context might discover that there are methods that are better able to predict CLV, although the added accuracy will most likely have to be acquired by sacrificing precious simplicity and convenience.

Additionally, further research is needed regarding the effect that lengthening the time horizon would have on the predictive performance of the models in a similar business context to that of Company X. Also, examining the effects of varying the length of the time period that the CLV forecasts are based on would offer very interesting and managerially relevant avenues for further research.

Finally, the models applied in this study overlook for example such important factors as the value of word of mouth and the actions of companies and other organizations that can be considered competitors. Including such factors in the CLV calculations remains a very interesting and relevant research opportunity in both an academic and also in a managerial sense.

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Appendix A: Full categorization of CLV models

Categorization of CLV models

Study	**Customer relationship**	**Application**	**Context 1**	**Context 2**	**Measurement technique**	**Level of aggregation**	**Main outcome or contribution**
Dwyer 1989	B2C	Illustrative only	Noncontractual	Always-a-share	Stochastic	Company	A migration model that predicts purchase behavior based on purchase recency.
Blattberg and Deighton 1996	Not applicable	Illustrative only	Not applicaple	Lost-for-good	Deterministic	Company	A model for balancing acquisition and retention spending.
Berger and Nasr 1998	Not applicable	Illustrative only	Not applicaple	Both	Deterministic	Company	5 practical models for calculating CLV.
Pfeifer and Carraway 2000	B2C	Illustrative only	Noncontractual	Always-a-share	Stochastic	Company	A generally applicable Markov Chain Model that can also be used in a migration context.
Rust et al. 2004	B2C	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A CLV model taking into account the effect of competitors’ offerings and brand switching.

Fader et al. 2005	B2C	Empirical application	Noncontractual	Lost-for-good	Stochastic	Company and individual	Develop a more easily implemented version of the Pareto/NBD model.
Lewis 2005	B2C	Empirical application	Contractual	Always-a-share	Stochastic	Individual	Calculating CLV using Dynamic Programming.
Reinartz et al. 2005	B2B	Empirical application	Noncontractual	Lost-for-good	Stochastic	Individual	Both the amount of marketing expenditure and how it is spent in a customer relationship are directly related to customer acquisition, retention and profitability.
Haenlein et al. 2006	B2C	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	Synthesis of CLV and real options analysis in customer relationship valuation.
Kumar et al. 2006	B2C	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	CLV can be used to calculate individual customer value in a retail context and is a useful metric for marketing resource allocation at the store level.
Haenlein et al. 2007	B2C	Empirical application	Noncontractual	Always-a-share	Stochastic	Segment	A model combining a Marcov Chain Model with Classification And Regression Tree analysis.

Venkatesan et al. 2007	B2B	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A model based on Bayesian decision theory used for selecting which customers to contact at a given period in order to maximize profit.
Borle et al. 2008	B2C	Empirical application	Contractual (membership)	Lost-for-good	Stochastic	Individual	A hierarchical Bayes approach for modeling CLV by predicting a customer's expected spending pattern.
Kumar et al. 2008	B2B	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	CLV-based reallocation of marketing resources led on average to a tenfold increase in revenue in the customer sample.
Ryals 2008	B2C and B2B	Empirical application	Contractual	Not applicable	Deterministic	Individual	An extension of CLV and CE to include the value of advocacy.
Homburg et al. 2009	B2C and B2B	Empirical application	Noncontractual	Always-a-share	Stochastic	Segment	An extended Markov Model for analysis of customer dynamics between segments.

Jen et al. 2009	B2C and B2B	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A model allowing for purchase timing and quantity decisions to be treated as dependently realized variables.
Kumar et al. 2010	B2C	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	In addition to CLV also Customer Referral Value should be calculated.
Braun et al. 2011	B2C	Empirical application	Contractual	Lost-for-good	Stochastic	Individual	A hierarchical competing-risk model for identifying the best targets for retention tactics.
Schweidel et al. 2011	B2C	Empirical application	Contractual	Always-a-share	Stochastic	Individual	Model for the analysis of customer's service portfolio dynamics in a multiservice company
Rust et al. 2011	B2B	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A simulation-based model for optimal marketing resource allocation.
Ascarza and Hardie 2013	B2C	Empirical application	Contractual (membership)	Always-a-share	Stochastic	Individual	Simultaneous modeling of usage and renewal
Romero et al. 2013	B2C	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A relatively flexible stochastic model.
Schweidel and Knox 2013	Nonprofit	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A model that accounts for the impact of direct marketing on customer behavior and value.

Esteban-Bravo et al. 2014	B2B	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A stochastic dynamic programming model for customer base CLV maximization using both individual and mass marketing interventions.
Ekinci et al. 2014 [1]	B2C	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	A relatively simple model for calculating CLV and optimal marketing resource allocation.
Jahromi et al. 2014	B2B	Empirical application	Noncontractual	Always-a-share	Stochastic	Individual	Application of data mining techniques to churn models.