A customer lifetime value model for the banking industry: a guide to marketing actions

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A customer lifetime value model for the banking industry: a guide to marketing actions

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Abstract

Purpose – The aim of this study is to develop an applicable and detailed model for customer lifetime value (CLV) and to highlight the most important indicators relevant for a specific industry – namely the banking sector.

Design/methodology/approach – This study compares the results of the least square estimation (LSE) and artificial neural network (ANN) in order to select the best performing forecasting tool to predict the potential CLV. The performances of the models are compared by the hit ratio, which is calculated by grouping the customers as "top 20 per cent" and "bottom 80 per cent" profitable.

Findings – Due to its higher performance; LSE based linear regression model is selected. The results are found to be highly competitive compared with the previous studies. This study shows that, beside the indicators mostly used in the literature in measuring CLV, two additional groups, namely monetary value and risk of certain bank services, as well as product/service ownership-related indicators, are also significant factors.

Practical implications – Organisations in the banking sector have to persuade their customers to use certain routine risk-bearing transaction-based services. In addition, the product development strategy has a crucial role to increase the CLV of customers because some of the product-related variables directly increase the value of customers.

Originality/value – The proposed model predicts potential value of current customers rather than measuring current value considered in the majority of previous studies. It eliminates the limitations and drawbacks of the majority of models in the literature through simple and industry-specific method which is based on easily measurable and objective indicators.

Keywords Artificial neural network, Least squares estimation, Customer lifetime value, Linear regression, Marketing decision

Paper type Research paper

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1. Introduction

The real purpose of business is now widely accepted to be creating and sustaining mutually beneficial relationships with selected customers (Ryals and Knox, 2005). Therefore, more and more companies today are focusing on establishing and maintaining good customer relations during each customer's lifetime with the company and subsequently generating higher profitability and growth. As a result of this approach, marketing activities and performance evaluations are increasingly being organised around relationships with customers rather than around products (Claycomb and Martin, 2002). As Kumar *et al.* (2004) state, the challenge for a company today is to implement an optimal blend of differential levels of customer treatment to maximise profits. Undoubtedly, one of the tools for identifying the value or profitability of customers is customer lifetime value (CLV).

Due to its growing importance, many researchers have devoted their attention to analysing CLV, especially since the last decade. Some of these studies related to CLV in the literature have focused on developing models to measure and predict CLV for different customer segments (Malthouse and Blattberg, 2005; Donkers *et al.*, 2007; Hwang *et al.*, 2004), while others have been mostly conceptual in nature and have discussed the role and impact of various predictors used to measure CLV (Ryals and Knox, 2005; Helgesen, 2006; Haenlein *et al.*, 2007; Ho *et al.*, 2006).

In the first group of studies, there is no standard way of measuring CLV, and existing research has some limitations concerning the real-world application of the proposed methods. As Jain and Singh (2002) emphasise, robust, simple, flexible, and empirically valid models are still very scarce in the literature. They also state that all models are not applicable to all product categories and, as mentioned by Haenlein *et al.* (2007), they may also differ substantially across industries and countries. Although such differences need to be translated and represented in the measurement of CLV, most previous studies lack the proposed models considering such differences.

On the other hand, in the second group of studies, which are conceptual in nature, only a few papers propose an extensive list of general as well as industry-specific indicators for CLV. Therefore, a more comprehensive and objective-oriented list of indicators should be developed. In fact, such an accurate list is also of primary importance for the first group of studies which focuses on building a model to measure the CLV.

In light of these limitations in the literature, the aim of the present study is to highlight the common indicators relevant especially for the banking industry and to develop a simpler and more applicable model for CLV that can be used in the banking industry. The paper consists of six sections. Section 2 presents a brief introduction to the concept of CLV, while Section 3 explains the role and application of CLV in marketing decisions. In Section 4, the indicators and the CLV measurement models developed so far in the literature are summarised. Section 5 presents the proposed methodology for measuring CLV, and Section 6 completes the paper with conclusions and future research.

2. The concept of customer lifetime value

Relationship marketing, as a marketing approach, and its management application, customer relationship management (CRM), require a paradigm shift in marketing management (Gummesson, 2004). CRM means that companies manage relationships with individual customers with the aid of customer databases and interactive and mass customisation technologies (Peppers and Rogers, 1999). The main idea of CRM is the assumption that customers differ in their needs and in the value they generate for the company. This leads to the result that CRM is not about offering every single customer the best possible service, but about treating customers differently depending on their CLV (Haenlein *et al.*, 2007). CLV can be defined as the present value of all future profits obtained from a customer over his or her relationship with a company (Gupta *et al.*, 2006). For this reason, CLV measurement is of crucial importance for companies in managing demand more effectively than do their competitors.

CLV measurement is easier and more applicable for companies that maintain continuous relationships with a substantial percentage of customers and that can customise marketing "investments", at least to some extent, across customers. Such companies include hotels, airlines, credit-card companies, banks and financial service providers, companies that sell over the internet, telecommunications companies, catalogue merchants, retail stores with "loyalty/frequent-shopper" programmes, publishers, and computer companies that sell direct to consumers. These kinds of companies operate mostly in the service industries and are also called "database marketing companies" in the literature (Malthouse and Blattberg, 2005). Although a true CLV measure implies measuring the customer's value over his or her lifetime, most encountered time periods for CLV analysis range from three to five years. As a matter of fact, there is much diversity in the research literature concerning both the measurement models to be used as well as the duration of the customer lifetime. Therefore, these two topics should be analysed in detail to develop and propose a model which eliminates the restrictions of the current models. It may be worthwhile to discuss the role and application of CLV in marketing decisions before analysing the different models developed for this purpose.

3. The role and application of customer lifetime value in marketing decisions

CLV analysis proposes that the value of a relationship with a customer can be increased either by increasing the amount of profit gained from the customer or by extending the enhanced relationship lifetime (Ryals and Knox, 2005). That is why different relationship marketing strategies are suggested for customers at different lifetime stages (Grönroos, 2007). For this reason, CLV is an important tool in determining the budget for marketing decisions and in helping companies make strategic as well as tactical decisions. Berger *et al.* (2002) state that companies must take four actions to allocate optimally the resources and to make the most appropriate marketing actions to acquire and maintain the relations with their customers:

(1) create a database-guided marketing intelligence capability for the calculation of CLV;

(2) segment their data according to customer needs and purchase behaviour, taking into account such factors as purchasing power, purchasing regularity, and the types of products purchased;

(3) forecast CLV under alternative scenarios; and

(4) allocate resources to maximize the value of the customer base.

The actions listed above also indicate that the most important role of CLV in marketing strategies is related to its role in the core strategic element of marketing management, namely segmentation and targeting, while allocation of the marketing budget and determining marketing actions and tactics accordingly represent the impact of CLV on tactical aspects of marketing. The following section presents the interaction between CLV and marketing strategy and tactics.

3.1 Segmentation and targeting

Market segmentation is one of the core concepts of marketing because different customer groups need different marketing mixes. Smith (1956) first defined market segmentation as "viewing a heterogeneous market as a number of smaller homogenous markets, in response to differing preferences, attributable to the desires of consumers for more precise satisfaction of their wants". Therefore, the main objective of segmenting markets is to satisfy customer needs and requirements by reaching each customer and allocating company resources to the most economically effective areas. In fact, ultimately, each person/customer represents a separate segment. Therefore, the core goal of considering the whole market as composed of smaller market segments is to develop different products and marketing activities that meet the needs of different market segments more effectively than those of competitors.

Although many attempts have been made to define the concept of market segmentation since the late 1950s, Smith's (1956) original definition remains appealing because of his insight that the derivation of market segments should be driven by a genuine heterogeneity in consumer needs and wants (Alfansi and Sargeant, 2000). Traditionally, companies have segmented their customers using four main groups of market segmentation criteria: geographic, demographic, psychographic, and previous purchase behaviour.

Despite the fact that demographic and geographic segmentation have been the most common traditional segmentation criteria, psychographic and behavioural criteria have been found to be better and more efficient indicators for defining the needs and wants, and therefore the purchasing behaviour, of customers in many industries.

Since the end of the 1980s, customer profitability has been accepted as an important basis for behavioural segmentation because of the central importance of profits. Mulhern (1999) stated that the use of CLV as a segmentation criterion has been found to be effective in helping organisations to target marketing efforts to the most lucrative market segments. Malthouse and Blattberg (2005) and Donkers *et al.* (2007) used two segments, namely the customers worth keeping (the retention segment), and those that are not worth the effort. In other studies using CLV, more advanced levels of segmentation have been proposed. These segments are based on customer profitability, such as a "best customers" segment, consisting of the highest-profitability customers for whom extensive retention programmes could be developed, and "less profitable customers", who are nonetheless similar to the best customers in the general characteristics of their purchasing patterns. For the latter segment, programmes to switch them to higher levels of profitability can be developed (Mulhern, 1999).

3.2 Resource allocation for marketing-mix elements and strategy formulation

Marketing-mix decisions involve the allocation of marketing budgets across customers or market segments. However, the main task of the marketing department, which is to increase short-term sales and long-term brand equity simultaneously, makes it difficult to measure the success of a given marketing effort. Formerly, the criteria most widely used to measure marketing performance were customer awareness, customer satisfaction, and loyalty. As Labbi and Berrospi (2007) emphasised, the related data are valuable, but do not address the financial impact. Undoubtedly, in today's highly competitive environment, marketing departments must consider in depth how effectively they spend their large budgets in terms of the degree to which the expenditure contributes to the profitability, growth, and long-term competitive advantage of the company. When a valid profitability measure is available, resource allocations can be made in a manner that maximizes the return on the marketing investment (Mulhern, 1999). Kumar and Rajan (2009) stated that an optimal allocation strategy evaluates customers based on their future profitability and recommends appropriate marketing initiatives. However, according to Donkers and Verhoef (2001), the potential as well as the current value of customers should be taken into consideration in allocating resources and determining effective strategies. Once the company decides which customers to contact, the second stage is to investigate the responsiveness of different segments of customers to various marketing actions. At the final stage, the right mixture of these channels is developed.

Quantitative approaches to marketing resource allocation have recently attracted increased research interest in both the marketing and data mining literature. Most studies in the literature have focused on developing quantitative models for optimal marketing budget allocation, rather than on conceptual discussions of the allocation of resources and the suggestions for the related marketing strategies. As an example of the first group, the study of Ching *et al.* (2004) proposed a model and found that when fixed promotion costs are high, the optimal strategy is not to undertake promotions to active customers, but to target promotion schemes to both inactive (purchasing no services) customers and competitors' customers. However, when fixed promotion costs are low, it is necessary to take care also of the low-volume customers to prevent this group of customers from switching to competitor companies.

Similarly, Labbi and Berrospi (2007) proposed a three-step methodology (customer segmentation, customer dynamics, and portfolio optimisation) to determine CLV by means of dynamic programming algorithms to identify which marketing actions are the most effective in improving customer loyalty and increasing revenue. They identified customer dynamics and tried to estimate CLV over variable time horizons through the integration of Markov decision-process models and Monte Carlo simulations. In the last step, they optimised the planning of campaign sequences for each customer profile. Labbi and Berrospi (2007) applied this methodology to an airline company, which reported a significant impact on the planning and cost of its marketing campaigns. The company moved from mileage-based management to value-based management of its frequent flyers. As a result, it was reported that marketing costs were reduced by more than 20 per cent and response rates were improved by up to 10 per cent.

Kumar *et al.* (2004) on the other hand, proposed an optimisation process that finds the optimum number of contacts made through each channel to each customer, in order to maximise the CLV of each customer or group.

All the discussions and quantitative studies mentioned above imply that the allocation of marketing budgets and the formulation of related marketing strategies and tactics should be evaluated in terms of their impacts on CLV. As Gurau and Ranchhod (2002) emphasised, through the ability to understand and segment customers based on value, companies will be better equipped to develop customer management strategies that focus on direct marketing sales, customer service, service-activity pricing, type and frequency of promotional campaigns, and channel decisions.

4. Indicators and measurement models for CLV in the literature

As discussed in the previous section, although CLV is an important and useful tool for developing effective marketing strategies and obtaining a competitive advantage in the market, there is no consensus concerning the indicators or measurement methods for CLV in the literature. Therefore, before developing and suggesting an alternative model for measuring CLV, it is necessary to examine and develop a more detailed list of existing indicators of CLV and to compare the models for measuring CLV that have been reported in the literature.

4.1 Literature review on CLV indicators

Predictors of CLV have been analysed and listed by various researchers in the literature (Blattberg and Deighton, 1996; Ho *et al.*, 2006; Ching *et al.*, 2004; Gurau and Ranchhod, 2002; Gupta *et al.*, 2006; Haenlein *et al.*, 2007; Mulhern, 1999; Hartfeil, 1996; Helgesen, 2006). Although some of these studies have emphasised common predictors or variables, there is no agreement on the remaining factors analysed due to the diversity of the industries investigated. The variables that are most widely used or discussed in the literature are listed below:

- Probability of a customer being alive in a given period (e.g. Kumar *et al.*, 2004).
- Customer acquisition and retention rates and costs (e.g. Blattberg and Deighton, 1996).
- Expenditures on marketing campaigns and maintaining customer satisfaction (e.g. Ho *et al.*, 2006).
- Expected revenue gained from a customer or group, derived from previous transaction data (e.g. Malthouse and Blattberg, 2005).
- Transition probabilities across groups or states (e.g. Ching *et al.*, 2004).
- Customer purchases, generally modelled as Poisson events, with their rates of occurrence depending on the degree of satisfaction of the most recent purchase encounter (e.g. Ho *et al.*, 2006).
- Customer satisfaction (e.g. Gurau and Ranchhod, 2002) has been shown to be a good predictor for the likelihood of repeat purchases and revenue growth by several studies (e.g. Ho *et al.*, 2006; Storbacka *et al.*, 1994). Satisfaction can be described by a Bernoulli distribution (e.g. Ho *et al.*, 2006).
- Recency-frequency-monetary (RFM) values of each customer's previous purchases (e.g. Gupta *et al.*, 2006). The recency value is the date of the customer's last purchase, the frequency value is the number of purchases by a customer in a given time period, and the monetary value is the amount of money spent by the customer in that period.
- Churn probability is the customer's probability of terminating his/her relationship with the company in a given time period (e.g. Ho *et al.*, 2006).

- Type and intensity of product ownership (e.g. Haenlein *et al.*, 2007).
- Customer's response level to campaigns offered shows whether the customer is active and has a potential to increase CLV (e.g. Mulhern, 1999).
- Age, demographic, and lifestyle characteristics of the customer (e.g. Haenlein *et al.*, 2007).
- Customer loyalty affects most of the other variables mentioned in this study and therefore is a predictor of CLV (e.g. Helgesen, 2006; Storbacka *et al.*, 1994).
- Macroeconomic environment and competition determine the activity level in the industry and the customer's brand-switching behaviour, which lead to changes in customer value generated at the company level (e.g. Gupta *et al.*, 2006).

The list of variables presented above indicates that the most commonly considered variables consist of profit-oriented or cost-oriented criteria. Although measuring CLV using these types of metrics and objective data available in company databases is very useful, consideration of other variables such as customer satisfaction, customer loyalty and product usage related variables is also necessary for companies with the aim of adopting a customer-oriented approach to the market.

4.2 Literature review on measurement models

In the literature, CLV is measured using deterministic or stochastic models. Stochastic techniques such as Markov chains are widely used in the literature to model CLV to manage customer relationships but the main challenge lies in defining the states and determining the probabilities of transitions between states (Dwyer, 1997; Haenlein *et al.*, 2007; Morrison *et al.*, 1982; Pfeifer and Carraway, 2000). When the definition of the states changes, then the transition-probability determinations must also be changed. Another challenge is defining the rewards vector. The reward of a state may not be fixed for all customers in that state, but generally there is a defined range.

For stochastic models, in order to compute CLV, it is necessary to predict whether an individual will continue to be active and what his purchasing behaviour will be (Jain and Singh, 2002). The Pareto/NBD model is widely used for non-contractual settings where transactions can occur at any point in time (Gupta *et al.*, 2006). Singh (2003) stated that the Pareto/NBD type models proposed in the CLV literature have limitations concerning the input data requirements. Such models might give misleading results if a string of data on customer transactions extending over more than two years is included as an input to the model.

Borle *et al.* (2008) used a hierarchical Bayes approach to estimate the lifetime value of each customer on each purchase occasion by jointly modelling the purchase timing, purchase amount, and risk of defection from the company for each customer. The method was used to advise a marketing company in cases where the times of each customer joining the membership and terminating it are known once these events have happened. CLV is predicted based on the available information at the time of joining. Each time a purchase occurs, the company updates the parameters based on the available information and updates its CLV prediction. Probabilistic models are generally based on many assumptions. Furthermore, these models are used in situations where the time at which the customer becomes inactive is unknown and where the customer can make any number of purchases at any time and can become inactive at any time. The major limitation of this type of model is the possibility of giving misleading results for very long customer purchase histories (Jain and Singh, 2002).

Recency-frequency-monetary (RFM) models, on the other hand, are well-known deterministic models in the CLV literature. In RFM models, a certain number of points are given according to the RFM values of previous purchases by the customer. Bult and Wansbeek (1995) defined the recency as the time period since the last purchase, frequency as the number of purchases made within a certain time period, and monetary value as the amount of money spent during a certain time period. There are many examples of studies in which different approaches and assumptions are used in RFM models (Roberts and Berger, 1999). For example, Hughes (1994) divided each RFM into quartiles. The latest purchase time of 20 per cent of customers was set to 5; a score of 1 indicated that the most recent transaction was a long time ago. Frequency and monetary values were also ranked using the same system. Stone (1995) analysed the value of customers owning credit cards and proposed that different weights should be assigned to the RFM variables depending on industry characteristics, concluding that the highest weighting should be for frequency and the lowest for monetary value. Shih and Liu (2003) used the analytical hierarchy process to determine the relative importance of the RFM variables in a hardware retailing company. The expert group consisted of three administrative managers, two sales managers, one marketing consultant, and five customers who had made at least one purchase. After finding the weights, but before determining the rankings by multiplying the weights by the R, F, and M values, the values were normalized. The R, F, and M values of a customer have proven to be powerful predictors, and RFM models are convenient to use, but they ignore the fact that consumers' past behaviour may be a result of companies' past marketing activities, and they provide a score rather than a monetary value (Gupta *et al.*, 2006).

By contrast, deterministic models have important limitations compared to stochastic models. They treat the profit margin for products as fixed, and therefore it is difficult to forecast the future spending probabilities of customers by product. On the other hand, when the profits of the usages of products are summed up, the error terms are also summed up, and the degree of success of the model decreases.

Data-mining models can overcome some of the limitations of traditional deterministic models by forecasting the variables used in these models. As in the study of Gelbrich and Nakhaeizadeh (2000), they can also be used directly to forecast the CLV itself. Donkers *et al.* (2007) tried to estimate the CLVs of the customers of an insurance company by means of several data mining models. Bolton *et al.* (2000) examined the implications of loyalty-programme membership and service experiences for customer retention and value. They developed a model of the influence of a loyalty rewards programme on customers' decisions to repurchase a service and their decisions about how much to use the service. Malthouse and Blattberg (2005) considered linear regression with variance-stabilizing transformations estimated using ordinary least squares (OLS), a technique for estimating the unknown parameters in a linear regression model. Once a final model had been selected, they evaluated its predictive accuracy in two ways. The first was the familiar coefficient of determination (R^2), and the second was based on a classification table. One of the goals of CLV is to separate the "best" customers from the others. The approach assumes that the top 20 per cent based on actual CLV values in the target period are the "best" customers.

Malthouse and Blattberg (2005) used their estimated regression models to rank customers from best to worst. The 20 per cent with the largest predicted values were assigned to "best-customer" status and would receive perks. Benoit and Van den Poel (2009) also used regression models to forecast CLVs for a financial services company and showed that quartile regression outperformed traditional regression on both absolute and ordering-based predictive performance. The study showed that the smaller the top segment of interest, the better was the performance of quantile regression compared to least-squares solutions (Benoit and Van den Poel, 2009).

Data-mining models have been found to be efficient because they use many variables at one time and make the effect of each variable visible. However, sometimes past behaviour may not reveal the future behaviour of the customer, as in the example of students as today's low-value but tomorrow's potentially profitable customers. Therefore, accurate demographic data, and panel data need to be added to the currently used data set. Table I summarises and compares CLV-based studies from the literature.

As can be seen from Table I, most of the studies encountered in the literature are based on optimising CLV for a specific marketing decision such as promotional budgets, sales-force allocation, product recommendation, acquisition, or retention rate. Furthermore, most of the studies that simply predict potential CLV are based on many assumptions (e.g. Aeron *et al.*, 2008; Chan *et al.*, 2010; Jain and Singh, 2002; Venkatesan *et al.*, 2007). As stated by Jain and Singh (2002), most of the models lack empirical validation (for example, Liu *et al.*, 2007; Ho *et al.*, 2006). They also stated that most CLV models do not include demographic, product-usage variables, and deal with deterministic cash-flow streams from the customer (e.g. Berger and Bechwati, 2001; Ryals and Knox, 2005).

In the studies that simply predict CLV, the variables used are the type and intensity of product ownership (Gelbrich and Nakhaeizadeh, 2000; Haenlein *et al.*, 2007), customer activity level (Haenlein *et al.*, 2007; Jain and Singh, 2002), age, demographic, and lifestyle variables (Haenlein *et al.*, 2007), acquisition and retention expenses and probabilities (Jain and Singh, 2002), recency values (Jain and Singh, 2002; Shih and Liu, 2003), frequency values (Borle *et al.*, 2008; Gelbrich and Nakhaeizadeh, 2000; Shih and Liu, 2003), purchasing probabilities (Donkers *et al.*, 2007), customer income (Gelbrich and Nakhaeizadeh, 2000), customer lifetime (Borle *et al.*, 2008) and monetary values (purchase amounts and values are used in all of the studies).

In this study, the aim is to develop a robust model to predict customer value taking into account both the variables revealed from literature as well as from experts. Following the work of Benoit and Van den Poel (2009), Donkers *et al.* (2007), and Malthouse and Blattberg (2005), a regression-based relationship-level model is used to predict the potential values of individual customers. In fact, despite its simplicity, regression has shown good performance in a wide range of studies. Furthermore, the proposed model aims to eliminate the inadequacies mentioned by Jain and Singh (2002).

5. Methodology

CLV is the value of the customer's entire lifetime with the company; however, in the literature, forecasts usually focus on the next three to five years (Donkers *et al.*, 2007; Gurau and Ranchhod, 2002; Malthouse and Blattberg, 2005; Mulhern, 1999). Although Malthouse and Blattberg (2005) and Donkers *et al.* (2007) used one to five years' data to estimate customer value, they both concluded that the model results are better when

Table I.
Summary of previous studies

Reference	Methodology Deterministic models	Stochastic optimisation	Markov chains	RFM	Bayesian approaches (Pareto-NBD, hierarchical Bayes approach, Bayesian decision theory)	Literature review	Dynamic programming	Regression	Simulation and system dynamics	Application area	Limitations and future research
1 Ryals and Knox (2005)	✓									Relationship marketing strategy	Risk is thought of as churn probability but different factors can be considered for risk variables. The model is deterministic, it is based only on cash flow, but there is no forecast for future cash flows
2 Ho *et al.* (2006)		✓	✓							Optimal investment for LTV	There is no empirical validation and competition factor is not considered
4 Shih and Liu (2008)				✓						Product recommendation	–
5 Haenlein *et al.* (2007)			✓							–	Transition matrix is assumed to be stable in the future. It does not represent brand switching. It is based on the analysis of homogeneous groups instead of individual customers
6 Liu *et al.* (2007)							✓			Sales force allocation for marketing activities	There is no empirical validation
7 Kumar *et al.* (2004)	✓									The paper lists best practice applications	–
8 Jain and Singh (2002)	✓		✓		✓					–	There is no empirical validation; also it is based on many assumptions
9 Shih and Liu (2003)				✓						–	–
10 Berger and Bechwati (2001)	✓									Promotion budgetallocation	Model is deterministic. Different models for different markets and products should be studied. Synergy between acquisition and retention should be considered
11 Hwang *et al.* (2004)	✓									Customer segmentation	Profit margin taken is fixed for the products
12 Donkers *et al.* (2007)	✓							✓		–	The models should also be compared for other industries

(*continued*)

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13 Ching *et al.* (2004)		✓	✓							Advertising and promotion decision	
14 Pfeifer and Carraway (2000)		✓	✓							When to curtail the contact with the customer	
15 Blattberg and Deighton (1996)	✓									Optimal acquisition retention rates are found	
16 Gelbrich and Nakhaeizadeh (2000)	✓									–	A person is assumed to buy or drive a car until his death
17 Malthouse and Blattberg (2005)								✓		Top 20 per cent customers	The results of the regression models are successful but misclassification costs should be calculated and minimised
18 Benoit and Van den Poel (2009)								✓		Segmentation	The results of the regression models are successful. Different variables should also be taken into account
19 Jonker *et al.* (2004)		✓								Optimal marketing policy	–
20 Borle *et al.* (2008)					✓					Finding top 50 per cent customers	This model can be used for membership-based companies. Furthermore, it is based on many assumptions
21 Aeron *et al.* (2008)	✓								✓	✓	The model has the limitations of a deterministic model. Also the use of real data instead of simulated date would give more realistic results
22 Venkatesan *et al.* (2007)					✓					Customer selection for campaigns	It is based on many assumptions
23 Cheng and Chen (2009)				✓						Customer segmentation	Model should be assessed in finance, healthcare and service industries
24 Chan *et al.* (2010)									✓	–	The use of real data instead of some assumptions would give more realistic results

Table I.

the forecast period is short, namely one year. Additionally, since one of the aims of this paper is to propose an applicable model, the use of real data available in a specific organisation was necessary. In order to propose a realistic model, a one-year estimation-based approach is adapted because of the lack of data on a longer period in the selected company. In fact, the consideration of such a short period is not only a requirement but also a solution to severe forecasting errors that are frequent in the models incorporating predicted purchases farther in the future (Mulhern, 1999). Moreover, most companies make their marketing plans for the coming year. Therefore, the proposed model, based on a one-year forecast, is believed to be useful for companies. Figure 1 shows a flowchart of the proposed model.

The steps in implementing the proposed model are as follows:

- Step 1 – The variables that will be used in the customer annual-value prediction model are determined according to the literature survey and expert opinion for the banking industry under consideration.

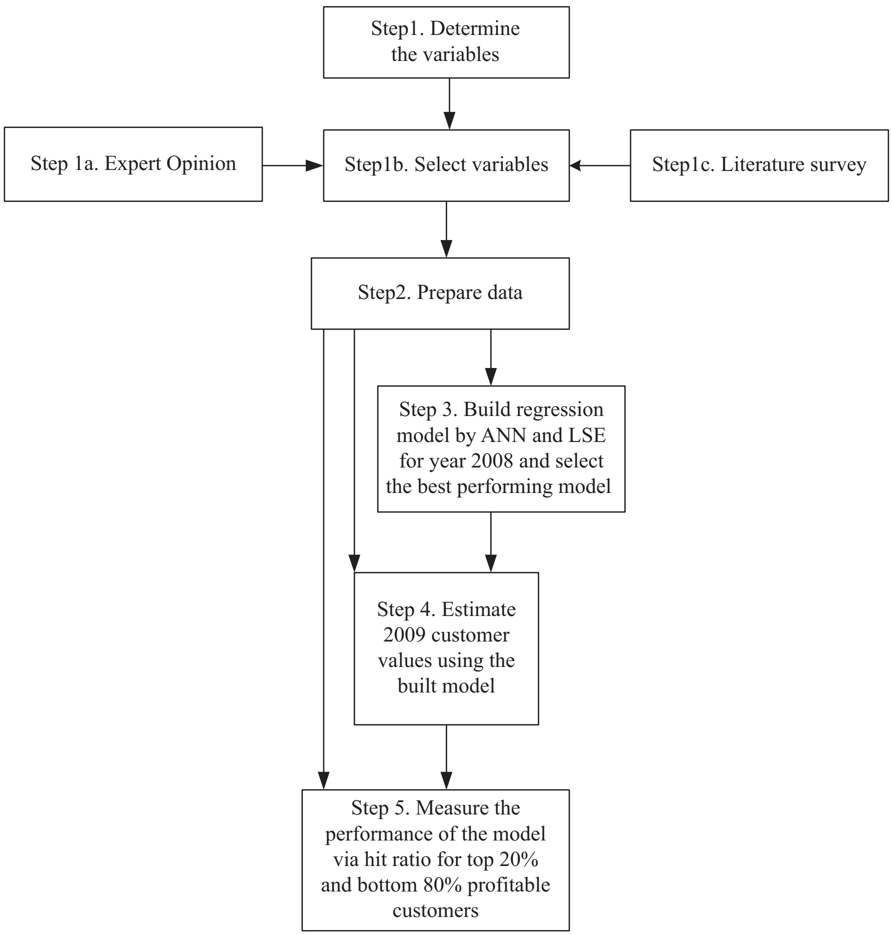

Figure 1.
Flowchart of the proposed model

- Step 2 – The selected variables are derived from the database for the years under consideration.
- Step 3 – Using the determined variables, regression models are built by both artificial neural network (ANN) (Hecht-Nielsen, 1988) and least-squares estimation (LSE) methods. In this step, 80 per cent of the data are taken as the training set and 20 per cent as the testing set. For this purpose, the average values over 12 months for each variable are initially calculated. The dependent variable is the yearly profit obtained from the customer and is computed as taking the sum of the profits gained from each transaction, the assets and liabilities and the products/services used by the customers. The performance of the models is measured by the hit-ratio criterion (Donkers *et al.*, 2007; Malthouse and Blattberg, 2005). Because one of the aims of CLV analysis is to identify the most profitable customers, the hit ratio is calculated based on the grouping of customers into the top 20 per cent and bottom 80 per cent of profitability. According to industry experience, the most profitable 20 per cent of customers are assumed to generate 80 per cent of the profits. Once the values of the customers have been predicted by means of a regression model, the ratio of the predicted top 20 per cent of customers to the actual top 20 per cent of customers and the ratio of the predicted bottom 80 per cent of customers to the actual bottom 80 per cent of customers are calculated. According to this evaluation, one or the other of the models is selected for Step 4.
- Step 4 – The regression model developed using the 2008 predictors is used to forecast 2009 values for the customers.
- Step 5 – The predictive accuracy of Step 4 is measured again using the hit-ratio criterion.

This proposed five-step methodology must also be validated in a real-life application to demonstrate its success and usefulness.

6. Application to the banking sector

Financial service markets are becoming more competitive because of technological developments and deregulation (Howcroft *et al.*, 2007). For this reason, banks need to build strategies for customers based on their values. The dataset consists of the monthly data of 10,000 customers of a bank.

In Step 1, an exploratory study through in-depth interviews were conducted with experts from the 11 banks in order to understand the importance of each indicator, which is mostly discussed in the literature in measuring the CLV and to explore additional indicators relevant for the banking industry. Table II shows whether the experts approve the inclusion of the variable in a model for CLV measurement.

As can be seen from Table II, eight additional variables were also included to the study based on expert opinion. These are the money or other unpaid loans collected by the execution or legal terms, the age of the customer in the bank, credit loan refinancing probability, product usage in other banks, current property holding, the products that the customer is active, and the profitability of the customer for each product.

Although all of those variables were not used to measure CLV in the literature, they were seen significant indicators of CLV by the experts of specific industry-namely banking.

Table II.
In-depth interview results about the variables used for CLV measurement

	Exploratory study	Literature review	Present study
Variable	The variable perceived as important indicators of CLV by the majority of experts	The studies that use the variable for CLV measurement (the name of the variable used in the study)	The variables used in this study[a]
Product/service types that customer used so far	+	E.g. Ho *et al.* (2006) (product usage), Haenlein *et al.* (2007) (product ownership type and intensity)	Product related variables: types of products number of products types of product groups number of product groups new product usage behaviour
Cross-sell, up sell trends of the customer	+	E.g. Ho *et al.* (2006), Haenlein *et al.* (2007)	Not available in the data set
Churn probability	+	E.g. Ho *et al.* (2006), Hartfeil (1996)	Not available in the data set
Frequency value	+	E.g. Gupta *et al.* (2006)	Not applicable
Demographics data	+	E.g. Haenlein *et al.* (2007)	Not available in the data set
Customer acquisition/retention probabilities	+	E.g. Blattberg and Deighton (1996)	Not available in the data set
Profit gained from each transaction	+	E.g. Gupta *et al.* (2006) (profit gained from customer's transactions)	Profitability of the customer (dependent variable)
Monetary values of each product/service used by the customer	+	E.g. Gupta *et al.* (2006) (price paid by a customer at time *t*)	Monetary values: total assets values of the specific services used by the customer (checking and saving accounts, EFT, credit card, loans, etc.) in local currency value of them in foreign currencies
Customer loyalty level	+	E.g. Helgesen (2006)	Not available in the data set
Recency value	+	E.g. Gupta *et al.* (2006)	Not applicable
Early loan or line of credit pay down probability	+	E.g. Helgesen (2006)	Not available in the data set
Default of payment probability	+	E.g. Hartfeil (1996) (credit risk)	Monetary risk: risk of default of loan payments (loans and credit card)

(*continued*)

	Exploratory study	Literature review	Present study
Customer satisfaction level	+	E.g. Gurau and Ranchhod (2002), Ho *et al.* (2006)	Not available in the data set
Customer's response level to campaigns offered	+	E.g. Mulhern (1999)	Not available in the data set
Operational cost per customer	+	E.g. Gupta *et al.* (2006)	Not available in the data set
Probability of a customer being alive in a given period	+	E.g. Kumar *et al.* (2004) (the probability of customer being active)	Activity level of the customer
Macroeconomics environment factors	+	E.g. Gupta *et al.* (2006)	Not available in the data set
Competition level	+	E.g. Gupta *et al.* (2006)	Not available in the data set
Marketing campaign/promotion expenditures	+	E.g. Ho *et al.* (2006)	Not available in the data set
Customer acquisition/retention costs	+	E.g. Blattberg and Deighton (1996)	Not available in the data set
Customer satisfaction expenditures	+	E.g. Gurau and Ranchhod (2002)	Not available in the data set
The money or other unpaid loans collected by the execution or legal terms	+		Not available in the data set
Operational risk (fraud, etc.)	+		Not available in the data set
Age of the customer in the bank	+		Not available in the data set
Credit loan refinancing probability	+		Not available in the data set
Product usage in other banks	+		Not available in the data set
Current property holding	+		Product related variable: the total value of the salary payments
The products that the customer is active	+		Product related variables: the number of active product groups owned the number of active products owned
The profitability of the customer for each product	+		Not available in the data set

Note: [a]The nature and types of the variables rather than their exact names are given due to the confidentiality principles of the company

Table II.

After the specification of the variables, their availability in the data warehouse of the selected bank is also investigated. As a result, 24 variables were selected as the main indicators of CLV in this study. Among the indicators listed in section 4.1, customer satisfaction and competition-related indicators were not included in the selected set of variables due to the lack of data. On the other hand, recency and frequency measures are not also taken into consideration due to the inapplicability of these indicators for the multiproduct case. Finally, demographic and lifestyle variables cannot be used in the study due to the fact that the unreliability of data found in the data warehouse of the selected organisation. Indicators related to the macroeconomic environment are not also included among the 24 variables because their incorporation necessitates the use of an econometric model. The selected variables can be classified as activity level variable (one variable), total assets (one variable), and three groups of other variables, namely:

(1) monetary values (12);
(2) monetary risks (two); and
(3) product-related variables (eight).

Based on the selected group of variables, the main hypothesis of the study is defined as follows:

H1. The CLV of each customer depends on the activity level, on total assets of customer's all banking operations, the monetary values of all the services used by customer, the monetary risk of the all banking operations realised by the customer, and the customer's product usage and ownership.

Where:

H1.1. The CLV increases as the activity level, total assets of customer's all banking operations, monetary values of all the services used by customer increases.

H1.2. The CLV does not increase as monetary risk of the all banking operations realized by the customer increases.

In Step 2, the average values over 12 months were determined for all variables, and annual profits were calculated for 2008 and 2009.

In Step 3, the R^2 of the LSE model for 2008 was calculated as 0.952 for the test set, which means that 95.2 per cent of the variance in the dependent variable can be predicted from the independent variables, while the R^2 for the ANN model was found to be 0.894 (the least mean squared error, i.e. 0.00031892, was found for one hidden layer with two neurons). Although the R^2 value of the ANN model was lower than that of the LSE model, to be sure about which model was better, a classification table was also built and is shown in Table III. (PASW Statistics 18 was used to calculate the LSE regression model and MATLAB Neural Network Toolbox was used to calculate the ANN model.)

Table III shows that of the top 20 per cent most profitable customers, 8.8 per cent would not be identified by the LSE model, while 9.7 per cent would not be identified by the ANN model. Similarly, 2.2 per cent of the least profitable (bottom 80 per cent) customers were misclassified by the LSE model and 2.4 per cent by the ANN model. The existence of multi-collinearity was also tested by calculating the VIF values and it was found that all of them were below 3.00. Therefore it was decided that there is no evidence about the existence of multi-collinearity. As a result, the LSE model was selected to be used for potential CLV prediction. The 12 variables included in the model were from the monetary-values group; eight of them were product-related variables, two came from the group of monetary-risk variables calculated from earlier studied models, one was total assets and one was the activity level of the customer. A summary of the model is given in Table IV. Monetary value-related variables are concerned with various types of banking services such as lending and credit cards. Risk-generating banking services such as loans are integral parts of the monetary risk-related variables. As a response to the criticism of previous models made by Jain and Singh (2002), product-related variables, including the type of and number of products, product groups, and new products, were also admitted as core variables of the model.

The mathematical formulation of the final model is:

$$\text{Value of customer } i = -7.315 + 20.01X_{\text{activity level of customer } i} + 0.009X_{\text{total assets of customer } i} + \ldots 0.009X_{\text{product related variable 8 of customer } i},$$

where X_{variable} is the value of the variable.

The analysis indicates that *H1* is accepted since all of the variables are found to be significant. The findings reveal that the monetary value of certain routine and widely used services increases customer value, which supports *H1.1*. *H1.1* is supported except for the two monetary value variables. Additionally it is seen from the results that activity level and total assets of customer have positive coefficients, supporting *H1.1*. However, *H.12* is not supported by the model since the two monetary-risk variables have positive coefficients in the model. This shows that if the customer has a risk of being default of payment, the banks gain some profit from this situation also; the customer has to pay more to the bank since late payments are subject to some interest. Thus, the inclusion of monetary risk variables which have been ignored in previous research is an important contribution of this study.

The predictors that are found to be negatively associated with customer value are two of the monetary value variables and five of the product related variables. In fact these are the variables about services and products that the bank does not charge some fee to its customers, but has to spend some money. In fact, it is necessary to underline that this result may change from one consumer segment to another. The analysis also

	Actual		
Predicted	Bottom 80 per cent	Top 20 per cent	Total (per cent)
Bottom 80 per cent			
ANN	0.975	0.024	100
LSE	0.977	0.022	100
Top 20 per cent			
ANN	0.097	0.903	100
LSE	0.088	0.912	100
Total (per cent)	100	100	

Table III. Classification table of actual and predicted 20-80 per cent groups for 2008 customer values

Variables	Unstandardized coefficients B	SE	Standardized coefficients Beta	*t*	Significance
(Constant)	−7.315	6.882		−1.063	0.288
Activity level of the customer	20.01	2.641	0.02	7.575	0
Total assets	0.009	0.001	0.068	7.059	0
Monetary values					
Monetary value 1	0.203	0	0.733	482.93	0
Monetary value 2	−0.129	0.002	−0.087	−59.29	0
Monetary value 3	0.111	0.005	0.035	24.079	0
Monetary value 4	0.413	0.009	0.066	44.413	0
Monetary value 5	0.005	0.001	0.095	8.721	0
Monetary value 6	0.015	0.002	0.013	8.658	0
Monetary value 7	0.013	0	0.169	34.561	0
Monetary value 8	0.04	0.005	0.566	7.766	0
Monetary value 9	0.027	0.002	0.427	17.745	0
Monetary value 10	−0.064	0.006	−0.909	−11.62	0
Monetary value 11	0.436	0.018	0.038	23.942	0
Monetary value 12	0.011	0	0.305	87.121	0
Monetary risks					
Monetary risk 1	196.39	33.541	0.009	5.855	0
Monetary risk 2	375.26	54.828	0.01	6.844	0
Product related variables					
Product related variable 1	−26.525	5.672	−0.011	−4.677	0
Product related variable 2	−0.008	0.003	−0.004	−2.468	0.014
Product related variable 3	−0.047	0.01	−0.008	−4.581	0
Product related variable 4	94.28	13.725	0.071	6.869	0
Product related variable 5	−34.703	9.221	−0.025	−3.763	0
Product related variable 6	226.38	32.148	0.01	7.042	0
Product related variable 7	34.544	7.955	0.03	4.343	0
Product related variable 8	−76.652	13.233	−0.064	−5.793	0

Table IV.
Model summary

indicates that some of the variables in a single category have positive coefficients, while others have negative coefficients. For instance, some of the product-related variables have contradictory effects on CLV, for example overdrafts. This might imply that the value of customers varies based on their experience with certain products or product categories.

In Step 4, the regression model developed using the 2008 predictors was used to forecast the 2009 values of the customers, with the predictive accuracy measured by the hit-ratio criterion (Donkers *et al.*, 2007; Malthouse and Blattberg, 2005). The ratio of the top 2,000 customers predicted by the model to the actual top 2,000 customers was calculated and can be seen (Table V) to be similar to the classification table in Malthouse and Blattberg (2005).

Table V shows that among the top 20 per cent most profitable customers in 2009, 21 per cent would not be identified by this model. Similarly, 5.25 per cent of the least profitable (bottom 80 per cent) customers were misclassified. In comparison with the 20-55 rule (of the actual top 20 per cent, approximately 55 per cent will be misclassified) and the 80-15 rule (of the actual bottom 80 per cent, 15 per cent will be misclassified) stated in Malthouse and Blattberg's (2005) study, the results are highly competitive. This is probably because of the stable nature of the market, the customer composition and the inclusion of high number of indicators.

7. Conclusions and discussion

This study is an attempt to fill the gap of CLV-based researches by developing and testing a simple, empirically valid, and widely applicable model to measure CLV in a service industry, as an alternative eliminating the drawbacks of the previous models. For this purpose, regression analysis was conducted using both LSE and ANN techniques, and the performance of these two models was compared. The model proposed here includes not only profit and cost-oriented indicators, but also certain other indicators rarely used in the literature.

Because one of the aims of CLV analysis is to determine the most profitable customers, the performance of the models based on LSE and ANN techniques were compared using the hit ratio, which was calculated based on grouping the customers into the top 20 per cent and bottom 80 per cent, because the most profitable 20 per cent of customers are assumed to generate 80 per cent of the profits. Because of its higher performance in terms of the hit ratio, the LSE-based linear regression model which was found as more competitive than those in previous studies was selected.

The findings of the analysis indicate that profit-related variables such as the total value of frequently used routine banking services as well as cost-oriented variables and risk-bearing activity variables are the most significant indicators of CLV for each customer in the banking industry. Undoubtedly, the model proposed in this study confirms that the common, objective indicators discussed in the literature are significant and valid. Additionally, this study shows that two different groups of indicators, namely monetary value and the risk involved in certain banking services, as well as product and service ownership-related indicators, are also significant factors in measuring CLV. As the total value of routine banking services such as checking account, savings account, EFT, and the risk-bearing services such as credit card usage and loan increase, the CLV of the customer increases. Thus, the use of variety of bank services increases the value of the customers. For this reason the first requirement for increasing the CLV of customers for each bank, is to increase not only depth, but also width of the product mix. Subsequently, the bank needs to develop effective strategies to encourage their customers to use as much as different services offered to the market. Undoubtedly, cross-selling and up-selling campaigns, volume and quantity based promotion campaigns might be very effective to increase the use of risk-bearing services cited above. In addition, increasing availability by offering multiple channels

Predicted		Actual Bottom 80 per cent	Actual Top 20 per cent	Total
Bottom 80 per cent	Number of customers	7,580	420	8,000
	Hit ratio	0.9475	0.21	0.80
Top 20 per cent	Number of customers	420	1,580	2,000
	Hit ratio	0.0525	0.79	0.2
Total	Number of customers	8,000	2,000	10,000

Table V. Classification table of actual and predicted 20-80 per cent groups for one-year CLV might increase not only use of those services, but also facilitate the use of routine bank services.

Although product ownership and usage-related indicators have been generally neglected by researchers, this study points out that these factors significantly leverage the value obtained from customers. Among this group of indicators, the coefficient of product-related variable 4 supports our suggestion above by indicating a positive effect on the CLV. For this reason, the banks which are successful to add new products to their product mix and to develop effective strategies in order to facilitate the use of as many as these products actively, have more chance to increase the number of their profitable customers. Another significant result is the inclusion of monetary-risk variables, which were ignored by previous authors.

Most of the indicators which are found to have a significant impact on CLV are industry-specific factors. Thus, the model presented in this paper answers the criticisms of previous models made by Jain and Singh (2002) and Haenlein *et al.* (2007) by indicating that CLV measurement must be based on industry and product-specific indicators. It is obvious that organisations in the banking sector need to give priority to facilitating the use of certain routine risk-bearing and transaction-based services as well as to persuade their customers to use those services more frequently. This implies that the majority of traditional market-penetration strategies would be very useful for organisations to increase and maintain the lifetime value of their customers (Nielsen, 2002). In addition, product development as an intensive growth strategy has a crucial role in increasing the CLV of customers because some of the product-related variables directly increase the value of customers. This strategy would be implemented by using cross-selling and up-selling activities and developing customized promotional campaigns for each segment.

The model proposed for measuring CLV tries to eliminate the limitations and drawbacks of the majority of models in the literature through simple and industry-specific models with objective and easily measurable indicators. In addition, this model predicts the potential value of current customers rather than measuring their current value as in the majority of previous studies, making it a valuable tool for practitioners in the banking industry.

8. Limitations and future research directions

Although the model presented here eliminates some of the drawbacks of previous models and could easily be used by organisations in the banking industry, it also has its own limitations. The methodology proposed here considers only objective indicators and not the subjective ones such as customer satisfaction, perceived image, and loyalty. Although these factors are also of crucial importance for determining effective marketing strategies to provide customised services to customers, the data (including longitudinal data) on some of these subjective factors are generally obtained using cross-sectional research and are not integrated into current company databases. Very few models in the literature consider both acquisition and retention values as indicators of CLV in the same model. This model has also this limitation because of the unavailability of related data in the database of the selected company. Additionally, this model was developed for Turkish bank customers, and future research must test the model for bank customers from different cultures. Finally, longer time horizons can be tested and compared with the results of the current one-year forecast model.

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