ENHANCING CUSTOMER LIFETIME VALUE WITH PERCEPTUAL MEASURES CONTAINED IN ENTERPRISE INFORMATION SYSTEMS

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Abstract

Customer Lifetime Value (CLV) has been known and used in the marketing industry for many years. However, many contemporary Enterprise Information Systems (EIS) contain valuable additional data about customers that traditional CLV approaches do not consider to be evaluated. This paper proposes enhancement of the lifetime value model with perceptual metrics based on enhanced EIS data and opens up discussion about potential impact of such model.

1. Introduction, Related work, Literature

1.1. Customer Lifetime Value overview

Customer Lifetime Value (CLV) is determined as accumulated and appropriately discounted net contribution margin achieved per customer, once acquired (Paul D. Berger & Nasr, 1998). The term CLV was firstly mentioned in works of (Shaw, 1988), (Dwyer, Robert, 1989) and (Jackson, 1989). Shaw described CLV in context of database marketing. Dwyer showed lifetime value analysis used for a customer retention model and customer migration model. Jackson used the concept for appropriate valuation of customer acquisitions in insurance market.

Berger's model computes CLV using following formula:

$$CLV = \left\{GC * \sum_{i=0}^{n}\left[\frac{r^{i}}{(1+d)^{i}}\right]\right\} - \{M * \sum_{i-1}^{n}[\frac{r^{i-1}}{(i+d)^{i-0.5}}]\} \qquad \text{(Formula 1)}$$

Where

- *GC* is the (expected) yearly gross contribution margin per customer,
- *M* is the (relevant) promotion costs per customer per year,
- *n* is the length, in years, of the period over which cash flows are to be projected,
- *r* is the yearly retention rate of customer base and
- *d* is the yearly discount rate.

Assumptions used in this model are that (1) sales take place once a year, (2) both yearly spending to retain customers and the customer retention rate remains constant over time, and (3) revenues achieved per customer per year remain the same.

According to these assumptions and formula components, it is evident that CLV model have to be highly customized to company's needs and the type of customer purchase behaviour and intended application of CLV (Kumar, Ramani, & Bohling, 2004). One example of such differences is the time frame of retention when the customer if supposed to be active - e. g. eBay defines a customer to be active if she or he has bid, bought, or listed on its site during the past 12 months (Gupta et al., 2006).

(Gupta et al., 2006) presented six different approaches used for CLV modelling:

1. *Recency, Frequency, Monetary value (RFM) models.* This scoring model is implicitly linked to CLV, but predicts customer behaviour in the next period only and without providing a dollar number for customer value. RFM components are important past purchase variables that should be good predictors of future purchase behaviour.
2. *Probability models* takes use statistical stochastic processes in order to predict whether an individual will still be an active customer in the future. Pareto/NBD (Negative Binominal Distribution) model is a good benchmark model when considering non contractual settings where transaction can occur at any point in time.
3. *Econometrics Models* are used for modelling customer acquisition, retention and expansion and then combine them to estimate CLV. Gupta discusses the benefits of combined applications on profitability estimations given discounts a customer receives. Accelerated and proportional hazard models' role is to estimate permanent customer defection. Markov models estimate transition probabilities of a customer being in a certain state, when the customer is allowed to switch among competitors.
4. *Persistence Models* analyze the behaviour of different CLV components as a part of a dynamic system. Multivariate time-series methods are used for studying influence mechanisms and projection of the long-run or equilibrium behaviour.
5. *Computer Science Models* benefit from data mining, machine learning and nonparametric statistics in order to emphasize predictive ability with five different approaches: (1) projection-pursuit models, (2) neural network models, (3) decision tree models, (4) spline-based models (generalized additive models, multivariate adaptive regression splines, classification and regression trees) and (5) support vector machines. Gupta states three possible approaches to combination of models for predictive improvements: (1) machine learning with bagging, (2) econometrics with forecasts, (3) statistics, with weighting the predictions of different models.
6. *Diffusion/Growth Models* forecast the acquisition of future customers using disaggregated or aggregated customer data. These forecasts are used for estimation of Customer Equity that will be discussed later in this paper.

1.2. Differences between CLV and Customer Equity

Customer Equity (CE) is the sum of all expected contributions of all current customers (Blattberg & Deighton, 1996). The connection between CLV, Customer Equity and other forms of managerial point of view (Customer Value Management, Customer Asset Management, Customer Asset Value) was introduced in marketing and management literature in years 2002 – 2004 (mainly (Paul D. Berger et al., 2002), (Bolton, Lemon, & Verhoef, 2004) and (Hogan, Lemon, & Rust, 2002)). In comparison with CLV that serves mainly for operational marketing activities, CE is useful for strategic managerial decisions (Rust, Lemon, & Zeithaml, 2004).

1.3. CLV in current Enterprise Information Systems

There are multiple parts of Enterprise Information Systems (EIS) that either take part in the computation of CLV or serve as a target platform of CLV analysis output:

- *Enterprise Resource Planning* (ERP) contains all transaction and purchase records. Many financial data sources are required for CLV computation in order to include product margins and profits.
- *Customer Relationship Management* (CRM) with all customer-centric data is a great data source for CLV, containing customer interaction history used for RFM analysis, customer service and call centre records and important data about customer's contractual settings, if applicable. There are also some media channels that take part of Social CRM: (1) Social Network Analysis with data from social media (Facebook, Twitter, Pinterest, company blogs, forums etc.) and (2) Voice of Customer (customer feedback, Net Promoter Score surveys etc.).
- *Web Analytics* consist of both anonymous and identified data about visitor behaviour on company's websites and in mobile applications.
- *Enterprise Marketing Management* both as a data source and target platform. Campaign Management Systems hold data about (1) marketing plans and activities that can be used to include acquisition campaign costs, (2) campaign responses across different marketing channels. Marketing experimentation with a result of multivariate testing response can serve as a sensitivity and affinity indication. Multiple marketing applications benefit from CLV. As (Gupta et al., 2006) mention, researchers either build separate models for customer acquisition, retention, and margin or sometimes combine two of these components. Using CLV according to target application is straightforward, but lacks the benefit of Enterprise Information Systems that should allow sharing "one version of truth", i.e. integrated or consolidated CLV independent of context. (Thomas, 2001) showed how customer management decisions based only on an analysis of acquired customers can be biased and misleading, and calculated the financial impact of not accounting for the effect of acquisition on customer retention.
- *Data Mining*. The main researched Data Mining applications of CLV are various customer retention strategies (Gupta & Zeithaml, 2006), (Rosset, Neumann, Eick, Vatnik, & Idan, 2002).
- *Business Intelligence (BI) and Corporate Performance Management* (CPM). CLV and CE can be clearly connected to company financial performance (Bauer, Hammerschmidt, & Braehler, 2003), thus giving a place to CPM and BI. The role of CPM software is in this context to report, plan and forecast the Customer Equity and its relation to Shareholder value (P. D. Berger et al., 2006) using Balanced Scorecard or other methods. Research problem: CLV model critique

All six approaches for CLV modelling mentioned in part 1.1 focus on the use of transactional data from purchase behaviour (number of transactions, margin, purchase frequency and duration etc.) only. Very few literature sources are concerned with nonfinancial components of CLV calculation, yet many of them mention different behavioural and perceptual metrics that can and should be linked with lifetime value. (Blattberg, Malthouse, & Neslin, 2009) find that customer satisfaction, marketing efforts, cross-buying and multichannel purchasing all have positive relationships with CLV.

Blattberg's conceptual framework differentiates Exogenous Customer Characteristics (e.g. Demographics), free Customer Relationship characteristics ((1) Marketing Actions: Brand, Product, Price, Promotion and Distribution, (2) Affective Customer Responses: Attitudes and Satisfaction and (3) Behavioral Customer Responses: RFM, Cross buying and Multichannel) and CLV characteristics (Relationship, Duration, Revenue, Costs and Discount Rate).

Several other authors worked on incorporating customer satisfaction into CLV. (Ho, Park, & Zhou, 2006) extend CLV model to include satisfaction. Ho's work is based on the assumption that customer purchases can be modelled as Poisson events, and their rates of occurrence depend on the satisfaction of the most recent purchase encounter. Customers purchase at a higher rate when they are satisfied than when they are dissatisfied. (Ranaweera, 2007) doubted the premise that having long-term satisfied customers was the best predictor of having profitable customers. His results suggest that claims about the higher profit potential of "loyal" customers made in the literature are likely overstated.

Current CLV model approaches take into consideration only transactional behavioural values and no nonfinancial or perceptual measures. As (Lariviere, 2008) states, researchers had so far been investigating the direct influence of any single customer behavioural metric on customer financial metrics. The urgency of incorporating various customer attributes and variables is mentioned by (Chen & Dubinsky, 2003) in context of perceived customer value. His work proposes new variables relevant to an e-commerce setting and integrates several key variables into one model. Modern Enterprise Information Systems offer wide possibilities for customer value enhancements. Following part 3 will mention possible perceptual metrics.

2. Behavioural outcomes and Perceptual measures

The difference between customer behavioural and perceptual metrics was previously discussed by (Gupta & Zeithaml, 2006). Behavioural Outcomes are observed metrics that explains what customers are doing, while Perceptual Measures are unobserved and follow what customers are thinking. Both types of measures are influenced by what companies are doing (mainly in terms of marketing actions).

Combining the references of (Keiningham, Cooil, Aksoy, Andreassen, & Weiner, 2007) and (Gupta & Zeithaml, 2006) we obtain a list of perceptual measures used in Table 1.

Perceptual measure	**Possible data source in EIS**
Customer satisfaction. The link between the customer satisfaction and lifetime value is not direct. (Gurau, Ranchhod, 2002) researched that customer satisfaction influences customer loyalty, which in turn affects profitability.	CRM – Voice of Customer, Net Promoter Score.
Loyalty. Traditionally, loyalty has been measured behaviourally as repeat purchase frequency. Loyalty can also be measured attitudinally as repurchase intentions (as in (Reynolds and Arnold, 2000)), intention to recommend	CRM and Web Analytics.

to others, likehood of switching and likehood of buying more.	
Intentions to purchase or repurchase	Web Analytics.
Recommend intention	CRM – Voice of Customer, Net Promoter Score.
Perceived value	CRM – Voice of Customer.
Trust	CRM – Voice of Customer.
Commitment	Web Analytics and Enterprise Marketing Management.
Customer expectations and service quality	CRM – Customer support interactions.
Customer value (worth what paid for)	CRM and Web Analytics – Individual item feedback.
Brand preference	Social CRM – Social network analysis.

Table 1. Possible perceptual measures, based on (Keiningham et al, 2007) and (Gupta and Zeithaml, 2006)

Although many of perceptual measures should ideally be measured by qualitative research methods, current Enterprise Information Systems contain many interaction data that can serve as a direct or indirect computation of such measures. The reason behind this approach is that if we are not able to automate the measurement of perceptual aspects, we cannot use them in individual CLV calculations.

3. Possible CLV enhancement approaches

Enhancing CLV by additional measures has one simple managerial impact: should we have one value of a customer only? There are basically three possible approaches:

1. Use only behavioural CLV_b. All perceptual metrics would be considered supportive measures.
2. Use both measures: CLV_b and CLV_p next to each other.
3. Use the enhanced CLV_p only. The computation of CLV_p has to follow the rule $CLV_p \subseteq CLV_b$.

Options (1) and (2) share the approach of having one or more new metrics in work. This adds an additional complexity both into marketing operations (in terms of customer acquisitions and retentions) and into data analysis as well. Marketing processes has to redefine which measures to compute efficiency from. A new KPI has to be clearly distinguished from the old one. Many new metrics would cause problems to data visualization in Business Intelligence and Corporate Performance Management tools.

Using option (3) would affect the current view of customer's value and thus would be suitable mainly for companies with little experience with CLV.

The effect of perceptual metrics should be evident on final value. For this a system of weights would serve to initially customize the computation.

4. CLV enhancing proposal

As we presented in part 3, there are various data sources of perceptual measures that could serve as direct or indirect link to future behavioural measures. In this part we discuss possible CLV augmentations divided by channels.

- *Customer support.* The role of customer feedback is important for managing customer satisfaction. This feedback can be general to the whole company (as with Net Promoter Score) or feedback on every interaction (e.g. questionnaire after every food delivery).
- *Web Analytics.* Customer interactions on the company's website or in the mobile application are valuable source of:
    - behavioural RFM metrics (e.g. the last time a customer was on a website),
    - preferable device (what device a customer uses to access our services),
    - channel and content preferences (how does a customer react to email newsletters),
    - product affinity (e.g. what products a customer browses),
    - purchase intention (e.g. what products a customer adds to the basket),
    - content engagement (e.g. a customer leaving comments on interesting or controversial topics),
    - recommend intention (e.g. a customer sharing a page on social media sites).
- *Social media.* Various measures about the impact of user's opinions and recommendations were created across multiple social media sites, e.g. Klout (Anger & Kittl, 2011). Although Klout has been criticized heavily (Kastholm et al., 2012), it can help with two following signals: (1) how influential a customer is (i.e. how much would customer's satisfaction or dissatisfaction spread), (2) what type of social user a customer is (e.g. if she is an "influencer", should the company treat her differently?).
- *Geo-location services* (e.g. customer visits a store and checks in it without buying anything).

5. Next steps and further research

This paper identified various possible ways to enhance customer lifetime value, but hasn't provided any detailed computations and practical evaluations yet. There are many important questions for further research and improvement in this area.

1. How to validate our enhancing proposals? We will focus our work to theoretical behavioural simulations using what-if scenarios and to practical case-study applications on real-world companies.
2. Can a customer be strategically important while non profitable? The role of a customer that doesn't buy anything but gladly shares a word about a company in his social network.

3. Can Social Network Analysis be used to raise customer importance (e.g. a life partner of a very profitable customer)?
4. What impacts would a CLV_p have on marketing processes?
5. What parts of ICT should a company employ to support benefits of CLV_p?
6. What technological challenges would we face during the CLV_p computation and applications?
7. How to efficiently integrate all data sources for CLV computation?
8. How can CLV_p be linked with overall company performance?
9. Can a different model for CLV computation help to achieve competitive advantage for a company?
10. What industry specifics should be considered while using CLV_p?
11. What weighting system should be selected for full customization of the new model?
12. Can CLV_p be used both for customer acquisition and retention processes?
13. What time frames should be used for predicting CLV or benefiting from current value (i.e. what value a customer has with last order 10 years ago)?
14. How to integrate lifetime value into event-based marketing (e.g. a lowering CLV_p can be used to proactive marketing communications to a customer)?

This paper is a work-in-progress and feedback is welcome.

6. Conclusion

This article described how traditional CLV model approaches include transactional financial data only. It is clear that many of modern Enterprise Information Systems contain valuable data about customer's relationship.

Although there is currently no single clear way to include such data to CLV calculation, it is evident that various additional CLV enhancements can shed more light on customer behavior and the importance of individual customers to a company.

Many specific problems still have to be resolved in order to benefit from all customer interactions that can be considered as signals of customer value. We hope our proposed enhancements and discussion sparks new interest in this important area.

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