J. of the Acad. Mark. Sci. (2012) 40:387–401
DOI 10.1007/s11747-011-0263-4

CONCEPTUAL/THEORETICAL PAPER

Measuring customer profitability in complex environments: an interdisciplinary contingency framework

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Received: 5 January 2011 / Accepted: 1 June 2011 / Published online: 19 June 2011

Abstract Customer profitability measurement is an important element in customer relationship management and a lever for enhanced marketing accountability. Two distinct measurement approaches have emerged in the marketing literature: Customer Lifetime Value (CLV) and Customer Profitability Analysis (CPA). Myriad models have been demonstrated within these two approaches across industries. However, limited efforts have been made to explain *when* sophisticated CLV or CPA models will be most useful. This paper explores the advantages and limitations of sophisticated CLV and CPA models and proposes that the degree of sophistication deployed when implementing customer profitability measurement models is determined by the type of complexity encountered in firms' customer environments. This gives rise to a contingency framework for customer profitability measurement model selection and five research propositions. Additionally, the framework provides design and implementation guidance for managers seeking to implement customer profitability measurement models for resource allocation purposes.

Keywords Marketing accountability · Customer Lifetime Value (CLV) · Customer Profitability Analysis (CPA) · Customer Relationship Management (CRM) · Contingency theory · Interdisciplinary · Contingency framework · Behavioral complexity · Service complexity

We thank several professors from the accounting, finance and marketing departments of Copenhagen Business School and Georgia State University, and the Marketing Science Institute for providing feedback on the earlier versions of this manuscript. The participants on the 32nd INFORMS Marketing Science Conference in Cologne in June 2010 also provided valuable feedback on our work. We thank Renu for copyediting the manuscript. We thank the editor and the three anonymous reviewers for their guidance in revising this manuscript.

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Introduction

Marketing accountability is growing in importance as marketing managers are increasingly expected to demonstrate the financial consequences of marketing activities (see "MSI Research Priorities" 2008–2010 [MSI 2008]; 2010–12 [MSI 2010]). The ability to predict and measure marketing activities' impact on cash flows and thus ultimately on firm value has also been acknowledged as an opportunity for marketers to achieve more influence in boardrooms, and a Marketing Accountability Standards Board (MASB) has risen to support this ambition (see "MASB Year II Overview & Report" [2010]). To succeed on this the marketing discipline must look beyond its conventional boundaries and strive for an integrated interdisciplinary accountability perspective across the disciplines of marketing, finance, and accounting (e.g., Srivastava et al. 1998) where the measurement of financial outcomes is the focus (Berger et al. 2006).

One element of marketing accountability is the measurement of the financial value of customer assets for decision making purposes. Determining the financial value of customers facilitates the allocation of marketing resources in accordance with customers' contribution to firm value creation. This philosophy is not only at the core of customer relationship management (Boulding et al. 2005; Payne and Frow 2005), but it is also a way of identifying where marketing strategies and tactics potentially generate the highest return on investment, thereby making the financial impact of these strategies and tactics measurable (Rust et al. 2004). Approximating the financial value of customer assets satisfactorily thus becomes a critical element in the chain of marketing productivity.

Two fundamentally different approaches to measuring the financial value of customer relationships prevail: Customer Profitability Analysis (CPA) and Customer Lifetime Value (CLV). Whereas CLV deploys a *prospective* perspective on customer profitability, predicting future customer behavior and discounting derived lifetime cash flows, CPA deploys a *retrospective* profitability perspective, measuring costs and revenues per customer in a specific accounting period in the past (Pfeifer et al. 2005). Despite the fact that both approaches share a common purpose of identifying the most valuable customers for resource allocation decision making, CPA and CLV models have been researched remarkably autonomously in the marketing and management accounting literatures. Although a few recent reviews have explored the marketing/accounting interface between CPA and CLV models (Gleaves et al. 2008; McManus and Guilding 2008) no previous study has, to the best of our knowledge, investigated CPA and CLV models' strengths and limitations from an integrated perspective.

This is puzzling as the relevance of deploying both CLV and CPA models for profitability-based resource allocation across customers has been demonstrated in a series of case studies. However, whereas most CLV models have been investigated in direct marketing settings mainly in consumer industries (e.g., retailing and catalog sales), CPA models have mainly been demonstrated across different B2B industries (e.g., supply-chain distribution) and in settings with intermediary channels of distribution between vendors and end-users (e.g., consumer product manufacturing). Furthermore, both approaches apparently have some kind of use in financial services. These discrepancies lead to an important unaddressed issue: *In which customer environments will sophisticated CLV and CPA models be more useful to support resource allocation decision making across customer relationships?* Recent calls have been made for exploring the boundaries and limitations of CLV models (Gupta and Lehmann 2006; Gupta et al. 2006). Such inquiry is important to both marketing science and practice as a contingency theory of this kind can be used to explain as well as to prescribe the degree of sophistication required of CPA and CLV models for resource allocation decision making in different customer environments. This way marketers can focus on the specific drivers of customer value that are relevant in their particular business context, which in turn leads to better utilization of marketing resources and enhanced marketing productivity.

We therefore seek to explore this issue by investigating extant research in CLV and CPA measurement. We argue that selecting between sophisticated CLV and CPA models is a matter of establishing a proper fit between CLV and CPA model sophistication and the complexity faced in firms' customer environments. We hereby make two research contributions: First, we contribute to marketing research on customer profitability measurement models (CLV/CPA) by introducing a framework proposing how firms will adjust the degree of customer profitability measurement model sophistication depending on the type of customer complexity encountered in their task environments. We furthermore highlight some collective limitations in terms of neglected tax effects and customers' contribution to portfolio risk that may bias both CLV and CPA estimates of customer value in certain business contexts. Second, we contribute to contingency-based research by introducing two "customer complexity" constructs: customer behavioral complexity and customer service complexity. Both constructs may be useful for inquiries in other areas of contingency-based research. Additionally, we contribute to marketing practice by proposing a three-step guideline for how customer profitability measurement models should be developed and implemented in different business contexts based on the proposed framework.

The rest of the paper is organized as follows: First, we define the scope of CLV and CPA models and the determinants of CLV and CPA model sophistication, thereby identifying these modeling approaches' individual and collective strengths and limitations. Based on this we propose a contingency framework for adapting CLV/CPA sophistication to the complexity encountered in a firm's customer universe and subsequently derive five research propositions from this framework. All this leads to three avenues for future research, whereupon we discuss the managerial implications of our findings followed by a conclusion.

Customer profitability measurement model scope and sophistication

Customer profitability measurement models are means of quantifying an individual customer's or a group of customers' contribution to the financial performance of the firm. Hence, any customer metric incorporating financial outcomes such as profits or cash flows at the customer or segment level are to be included in this categorization.

Research on customer profitability measurement models has emerged along the lines of the prospective Customer Lifetime Value (CLV) approach and the retrospective Customer Profitability Analysis (CPA) approach. The CLV approach is by definition aligned with the forward-looking nature of resource allocation decision making. However, as stated by Jacobs et al. (2001, pp. 355–56): "[T]he primary value of historical data lies in prediction, which then aids the decision-making process about the future." Hence, the retrospective CPA approach is also potentially useful for decision support.

Customer profitability measurement model sophistication is not to be interpreted as a normative guideline per se, inferring that more sophisticated models are always better. Instead, model sophistication merely reflects the degree to which advanced techniques are being used by managers when estimating model parameters.

Customer Lifetime Value (CLV) model scope and sophistication

Customer Lifetime Value (CLV) is conceptually defined as: "the present value of all future cash flows obtained from a customer over his or her life of relationship with the firm" (Gupta et al. 2006). A range of models for estimating CLV has been advanced in the literature either conceptually or via case demonstrations. Examples of these contributions are outlined in Table 1 (see Gupta et al. 2006; Villanueva and Hanssens 2006 for CLV model reviews).

Table 1 shows how the techniques for estimating model parameters have been gradually developed throughout the evolution of CLV models. This journey has taken CLV models from their deterministic point of departure (e.g., Berger and Nasr 1998; Berger et al. 2003; Dwyer 1997) where retention rates, customer margins and other input related to customer behavior are entered directly into mathematical formulas (Villanueva and Hanssens 2006) toward stochastic models (e.g., Haenlein et al. 2007; Kumar et al. 2006) where probabilistic determination of customer choice is incorporated (Villanueva and Hanssens 2006).

Whereas the early contributions mainly discuss how to develop a CLV model that can be generalized, later approaches have demonstrated how the implementation of CLV models improves customer marketing strategies, which in turn may enhance firm financial performance, via empirical case studies (Kumar et al. 2008; Ryals 2005). Some studies have even taken the financial performance link one step further and demonstrated how CLV-based analysis can predict firm value (Gupta et al. 2004) and that customer strategies targeted at maximizing CLV can increase a firm's stock price (Kumar and Shah 2009).

These cases are convincing, but they are merely demonstrations performed in direct marketing settings across a couple of service-oriented industries. In order to determine whether the findings can be generalized to other business contexts it is necessary to explore the scope of CLV models and the determinants of CLV models sophistication.

A common trait in CLV model evolution is the strong focus on developing a forecasting mechanism that captures the dynamics of customer behavior. Generally, this concerns the estimation of three key drivers of CLV (Venkatesan and Kumar 2004): (1) the propensity for a customer to purchase from the company in the future, (2) the predicted product contribution margin from future purchases, and (3) the direct marketing resources allocated to the customer in future periods. Hence, CLV models are means of quantifying the expected gross cash flows generated by the firm's offerings in future transactions with customers after accounting for the direct marketing costs invested in generating these transactions and cash flows. Recently, arguments have been raised for expanding the scope of CLV measurement to incorporate the indirect value of customer referrals, and models for estimating referral value have been demonstrated (e.g., Kumar et al. 2010; Ryals 2008). Such an expanded scope yields a more holistic forecast of the future benefits derived from customer relationships.

An implication of their prospective forecasting focus is that CLV models will always provide some indication of the future growth potential embedded in servicing any given customer or segment. A less obvious implication is that CLV models, by ignoring all other SG&A costs except direct marketing, make two implicit assumptions: First, it is assumed that the firm's service capacity is fixed (and therefore cannot be adapted to customers' potentially different demands for service activities in future periods). Second, it is assumed that service resource requirements are homogeneous across customer relationships. In contexts where these assumptions are violated, CLV estimates will provide a biased approximation of customer relationship value as the cash flow component for customers that draw heavily on the firm's service capacity (e.g., due to frequent sales visits, frequent, small-scale deliveries to distant locations, time demanding technical service calls) will be overvalued while cash flows from customers that are less demanding to serve will be undervalued. The severity of this bias will depend on the diversity of customer service requirements as well as the flexibility of service capacity resources, i.e., the degree to which capacity can be adjusted to reflect the demand for service activities in future periods.

Important determinants of CLV model sophistication are the technique used for estimating model parameters and the level of aggregation at which the analysis is carried out

Table 1 Examples of Customer Lifetime Value (CLV) cases

Data and references	Application	Industry	Customer relationship	Estimation/ measurement technique	Level of analysis	Key conclusions
Dwyer (1997)	Illustrative Example	Catalog Retail	B2C	Deterministic/ Stochastic (migration)	Firm Average	CLV can be estimated via a "retention model" for "lost-for-good" buyer-seller relationships and a "migration model" for "always-a-share" relationships
Berger and Nasr (1998)	Illustrative Examples	N.a.	N.a.	Deterministic	Firm Average	Five general models are applicable for determining CLV in "lost-for-good" and "always-a-share" relationships
Gupta et al. (2004)	Empirical Cases	Internet Companies & Financial Services	B2C	Deterministic	Firm Average	Customer Equity (the sum of CLVs across extant and future customers) approximates firm value well and can be estimated based on publicly available data
Berger et al. (2003)	Empirical Case	Cruise Ship Company	B2C	Deterministic	Segment Average	Generating data for CLV estimation can be demanding but the insights developed improve marketing strategy decision making
Ryals (2005)	Empirical Cases	Financial Services	B2B & B2C	Deterministic	Segments/ Individual Customers	The implementation of CLV changes customer management strategies which can lead to improved firm performance
Ryals (2008)	Empirical Cases	Financial Services	B2B & B2C	Deterministic	Individual Customer w/ referrals	Indirect value (e.g., referrals) has a measurable monetary impact that must be considered in CLV-based customer management strategies
Pfeifer and Carraway (2000)	Illustrative Example	Catalog Retail	B2C	Stochastic (MCM)	Firm Average	Markov chain modeling (MCM) is a useful technique for estimating CLV in a "migration model" due to its flexible and probabilistic nature
Libai et al. (2002)	Illustrative Example	Retailing	B2C	Stochastic (MCM)	Segment Average	CLV should be managed at individual customer level. But a segment-level approach yields sufficient insights more cost efficiently than an individual-level CLV model
Haenlein et al. (2007)	Empirical Case	Financial Services	B2C	Stochastic (MCM)	Segment Average	The specific requirements of the retail banking industry from a CLV perspective can be fulfilled by combining MCM with Classification And Regression Tree (CART) analysis
Aeron et al. (2008)	Simulation Example	Financial Services	B2C	Stochastic (MCM)	Individual Customer	The stages in a credit card company's customer relationships can be modeled in a MCM model based on historical data to come up with CLV per customer
Venkatesan and Kumar (2004)	Empirical Case	High-Tech	B2B	Stochastic (Antecedents)	Individual Customer	A customer selection model based on nonlinear drivers of CLV outperforms other customer-based metrics in identifying the most profitable customers in future periods. Hence, designing resource allocation rules that maximize CLV will improve firm financial performance
Reinartz et al. (2005)	Empirical Case	High-Tech	B2B	Stochastic (Antecedents)	Individual Customer	Both the amount of investment and how it is invested in a customer relate directly to the acquisition, retention and profitability of that customer. A CLV framework must therefore integrate these dimensions to manage the embedded trade-offs optimally
Kumar et al. (2006)	Empirical Case	Retailing	B2C	Stochastic (Antecedents)	Individual Customer	CLV can be estimated at individual customer level even in a dynamic retail context with millions of customers. CLV is useful for retention and acquisition decisions as well as for store performance management
Kumar et al. (2008)	Empirical Case	High-Tech (IBM)	B2B	Stochastic (Antecedents)	Individual Customer	CLV-based reallocation of marketing resources yielded a $20 million revenue increase without any additional resource investment
Kumar and Shah (2009)	Empirical Cases	High-Tech & Retailing	B2B & B2C	Stochastic (Antecedents)	Individual Customer	A CLV-based framework can reliably predict firm value and marketing strategies targeted at maximizing CLV can increase firm value and thus ultimately stock price
Kumar et al. (2010)	Empirical Cases	Retailing & Financial Services	B2C	Stochastic (Antecedents)	Individual Customer w/ referrals	To maximize firm profitability it is critical to understand both drivers of CLV and "Customer Referral Value (CRV)" and manage customers accordingly

(segment or individual customers). Whereas deterministic models rely on qualitative input via decision calculus or similar techniques (e.g., Blattberg and Deighton 1996; Ryals 2005) for predicting the components of CLV, stochastic models deploy quantitative statistical modeling techniques (e.g., Haenlein et al. 2007; Venkatesan and Kumar 2004). Consequently, deterministic CLV modeling introduces subjectivity that could potentially have an impact on predictive accuracy of forecasts and potentially over-simplifies the causal relationships between marketing efforts and customer behavior (Kumar and George 2007). Additionally, stochastic CLV approaches allow modeling of complex customer relationship situations where algebraic solutions are not possible (Pfeifer and Carraway 2000). Consequently, CLV modeling based on probabilistic forecasting of CLV components can be considered more sophisticated than deterministic CLV modeling.

Moreover, model parameters can be estimated either at the aggregate or disaggregate level, with the aggregate approach estimating retention rates, customer margins and other behavioral input as averages across a cohort of customers (firm/segment level) and the disaggregate approach estimating model parameters at the individual customer level (Kumar and George 2007). In an aggregate approach (firm or segment) deployed in most of the earlier work on CLV (e.g., Berger and Nasr 1998; Berger et al. 2003; Blattberg et al. 2001; Dwyer 1997; Gupta and Lehmann 2003), it is assumed that the underlying distribution of customer value across the customers in the cohort remains unchanged in future periods (Kumar and George 2007). The individual approach (e.g., Donkers et al. 2007; Kumar et al. 2006; Kumar and Shah 2009; Reinartz et al. 2005; Venkatesan and Kumar 2004) by definition captures such heterogeneities and can thus be considered more sophisticated than aggregate, average firm- or segment-level approaches.

Customer Profitability Analysis (CPA) model scope and sophistication

Customer profitability is 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). Hence, as opposed to CLV’s asset valuation approach focusing on future cash flows, Customer Profitability Analysis (CPA) is based on accrual accounting profits earned in the past.

The advent of Activity-Based Costing (ABC), where resource costs are consolidated in activity cost pools and related to cost objects (products, customers, transactions, etc.) via activity cost drivers (Cooper and Kaplan 1988; Cooper and Kaplan 1991), introduced a novel framework that facilitated the assignment of a broader range of costs and assets to customers (Goebel et al. 1998; Smith and Dikolli 1995). Consequently, the more recent literature on CPA has involved the ABC technique, as can be seen in the examples of CPA case studies outlined in Table 2 (see Gleaves et al. 2008; McManus and Guilding 2008 for reviews of CPA models).

CPA based on the ABC technique has highlighted that substantial variation in customer service activities (in the broadest possible sense) makes the incorporation of cost-to-serve important when evaluating customer profitability (Guerreiro et al. 2008; Helgesen 2007; McManus 2007; Niraj et al. 2001; Noone and Griffin 1999). These insights generated by CPA have enabled firms to improve the management of customer relationships (Andon et al. 2003; Helgesen 2007; Kaplan and Narayanan 2001; Storbacka 1997), leading to improved firm performance (Kaplan and Cooper 1998).

Hence, CPA modeling has demonstrated the same advantages as CLV, albeit in different industries (with the exception of financial services where both approaches have been demonstrated as being a valuable resource allocation mechanism). Whereas CLV has been shown to add value in service-oriented direct marketing settings, CPA models have mainly been demonstrated in product-based industries in a direct B2B relationship (Helgesen 2007; Kaplan and Cooper 1998; van Raaij et al. 2003), in supply chain distribution (Niraj et al. 2001), or in a consumer product channel setting (Guerreiro et al. 2008). Again, this raises the issue whether some general determinants of CPA model effectiveness can be identified, and again we turn to the scope and sophistication of the models.

As is evident from the case studies outlined in Table 2, the key idea of CPA is that all revenues, costs, assets, and liabilities relevant to servicing customers should be assigned to the customer relationships that cause them. This wider scope of the profitability component in CPA models vis-à-vis CLV models implies that CPA models do capture the profitability effects of heterogeneous service capacity requirements across customers in flexible service resource settings that CLV models ignore. However, the retrospective nature of CPA models embeds the implicit assumption that customer behavior does not change radically over time. Hence, retention patterns are assumed to be homogeneous across customers, and purchasing amounts are assumed to be stable over time (i.e., limited expansion potential). In contexts where customer behavior is dynamic rather than static, CPA models will provide biased approximations of customer relationship value as the growth dimension for customers with substantial expansion potential and/or high loyalty (as reflected in long expected retention durations) will be undervalued, whereas disloyal customers with no expansion potential will be overvalued.

By adopting a frame of reference from product costing, CPA sophistication can be determined by the range of costs

Table 2 Examples of Customer Profitability Analysis (CPA) cases

Data and references	Application	Industry	Customer relationship	Estimation/ measurement technique	Level of analysis	Key conclusions
Bellis-Jones (1989)	Illustrative Examples	Consumer Product Manufacturing	B2B2C	Not Discussed	Individual Customers	CPA facilitates a mutually advantageous dialogue between vendors and their present and future customers by focusing on all the activities and derived costs associated with serving customer relationships
Storbacka (1997)	Empirical Case	Financial Services	B2C	Not Discussed	Segments	CPA-based customer segmentation forms a good starting point for the formulation of marketing strategies
Mulhern (1999)	Empirical Case	Pharmaceutical Products	B2B2C	Direct Costing	Individual Customers	CPA serves two key purposes: market segmentation and marketing resource allocation
van Raaij et al. (2003)	Empirical Case	Professional Cleaning Products	B2B	Full Costing	Individual Customers	Firms implementing CPA face a number of issues. These barriers can be dealt with through a six-step process
Kaplan and Cooper (1998)	Empirical Case	Industrial Manufacturing (Kanthal)	B2B	Activity-Based Costing (ABC)	Individual Customers	CPA can deliver customer profitability information that facilitates fact based negotiation of price and service levels with customers. This, in turn, improves firm financial performance
Noone and Griffin (1999)	Empirical Case	Hotels	B2B & B2C	Activity-Based Costing (ABC)	Segments	The issues faced by firms implementing an activity-based costing approach to CPA can be dealt with through a ten-step process
Niraj et al. (2001)	Empirical Case	Supply Chain Distributor	B2B	Activity-Based Costing (ABC)	Individual Customers	Many purchase characteristics can have opposing effects on gross margins and cost-to-serve which makes revenue a misleading driver of customer profitability in a supply-chain context
Kaplan and Narayanan (2001)	Illustrative Examples	Multiple	B2B & B2B2C	Activity-Based Costing (ABC)	Individual Customers	Understanding the drivers of net profitability per customer allows suppliers to take actions that transform unprofitable customers to profitable ones
Andon et al. (2003)	Empirical Case	Financial Services	B2C	Activity-Based Costing (ABC)	Segments/ Individual Customers	Insights from CPA changed the management of customer relationships. The process was anchored in marketing with limited involvement of the accounting department
Helgesen (2007)	Empirical Case	Order-Handling Industry	B2B	Activity-Based Costing (ABC)	Segments/ Individual Customers	CPA is a mandatory marketing performance metric for decision makers that are going to manage customer relationships in ways that benefit the organization and its stakeholders
McManus (2007)	Empirical Case	Telecom	B2C	Activity-Based Costing (ABC)	Segments	A segment-based CPA model showed how differences in profitability exist between customers living in different geographical regions
Guerreiro et al. (2008)	Empirical Case	Consumer Product Manufacturing	B2B2C	Activity-Based Costing (ABC)	Individual Customers	The measurement of cost-to-serve provides specific customer information that enables a more comprehensive CPA than when only measuring gross profit from products

included in the estimate across the value chain (Brierley 2008) and the level of detail deployed when accounting for cause-and-effect relationships between customers, activities, subsequent resource consumption, and derived costs and investments at the individual customer level (Al-Omiri and Drury 2007; Drury and Tayles 2005). Hence, CPA sophistication is mainly a function of the accuracy at which overhead resource costs that cannot be traced entirely to customers on a one-to-one basis are assigned to the individual customer level. The effort invested in estimating these cause-and-effect relationships more accurately is determined by the process at which overhead resource costs are first divided into activity cost pools and then driven to cost objects (Al-Omiri and Drury 2007). Hence, the greater a range of total SG&A costs, the more cost pools and cost drivers applied to account for SG&A costs at the customer level, and the more extensively resource drivers and duration drivers are being applied in this process, the more sophisticated can the CPA model of the firm be considered to be.

Collective limitations of CLV and CPA models

Two areas that impact firm value creation are severely underdeveloped in CLV as well as in CPA research. First, incorporating the tax effects on customer cash flows is beyond the scope of both approaches. Hence, firms operating under heterogeneous tax regulations, as would often be the case in multinational sales/marketing organizations, will undervalue customers in low-tax regimes and overvalue customers in high-tax regimes. Furthermore, different tax repatriation regulations across countries may have an impact on the timing of cash flows from customers across these geographies. All this in turn may lead to suboptimal resource allocation in multinational customer environments.

Second, most CLV and CPA models ignore customers' contribution to firm portfolio risk. All CLV models take the time value of money into consideration, as all models discount predicted future contributions from customers at some cost of capital. However, the treatment of risk associated with expected future cash flows across customer relationships has received limited attention. Based on the notion that customer-level risk is determined by the volatility and vulnerability of customer cash flows (Srivastava et al. 1998), Kumar and Shah (2009) provide a rare attempt of incorporating customer-level risk by combining the standard deviation of CLV estimates when randomly simulating CLV model parameters (volatility) and the average share of wallet per customer (vulnerability) into an individual customer risk estimate. Although an important extension, this method does not account for any diversification effects across the customer portfolio.

A contingency framework for customer profitability measurement model sophistication

Customer profitability measurement model sophistication addresses different dimensions of firm value creation. Whereas CPA model sophistication is determined by the level of detail by which service capacity resource consumption is approximated at the customer level, CLV model sophistication reflects how advanced expected future gross cash flows from customers can be predicted. Hence, although both CPA and CLV models can be useful for resource allocation purposes, the respective models will not be equally useful to deploy in different customer settings. This context specificity, where the appropriateness of sophisticated management techniques may be dependent on the circumstances in which they are deployed, calls for a contingency approach (Tillema 2005).

Insights generated by sophisticated customer profitability measurement models increase transparency regarding the financial attractiveness of different customer relationships. The models will therefore be increasingly valuable as managers' information-processing requirements concerning customers' behavior and demand for service activities increases. Environments where managers face substantial information-processing requirements can be characterized as "complex" (as opposed to simple) (Duncan 1972; Pennings 1975; Tung 1979). Decision making among high degrees of environmental complexity entails that managers must possess more knowledge and consider more options than in simpler environments (Sharfman and Dean 1991). Hence, a great variety of factors are perceived as relevant by managers making decisions in complex environments (Miller and Friesen 1983; Smart and Vertinsky 1984; Tan and Litschert 1994).

Complexity is one of three key dimensions in organizational task environments (e.g., Castrogiovanni 2002; Dess and Beard 1984; Emery and Trist 1965; Miller and Friesen 1978; Sharfman and Dean 1991) and can formally be defined as "the level of complex knowledge that understanding the environment requires" (Sharfman and Dean 1991). Cannon and St. John (2007) have recently argued that environmental complexity is a multidimensional construct composed by (1) the number of environmental components with which the firm must interact (following Aldrich 1979; Duncan 1972; Kabadayi et al. 2007; Tung 1979); (2) the heterogeneity, dissimilarity, or diffusion among the environmental components (following Castrogiovanni 2002; Child 1972; Dess and Beard 1984; Duncan 1972; Kabadayi et al. 2007; Simsek et al. 2007; Thompson 1967; Tung 1979); (3) the sophisticated or technical knowledge required to interact effectively with the particular components that are present in a firm's environment (following Aldrich 1979; Mintzberg 1979; Sharfman and Dean 1991).

Since customers constitute one of the main components that give rise to complexity in firms' environments (Bourgeois 1980; Duncan 1972; Kabadayi et al. 2007), "customer complexity" can be characterized as one important element in the general environmental complexity faced by firms. Based on the multidimensional conceptualization of complexity, a complex customer environment consists of many different customers with heterogeneous needs and where high technical intricacy is required to interact effectively with the customers and other stakeholders involved in the customer relationship management process. In order to serve a complex customer environment firms must deploy different customer strategies and utilize multiple channels of distribution/communication to satisfy different customer tastes and needs across markets (Miller and Friesen 1983). It is this differentiation of efforts that in turn makes the deployment of sophisticated managerial systems and processes necessary for managers in order for them to cope with increasingly complex decision making environments. This adaptation of decision making system sophistication to fit environmental complexity has found empirical support, e.g., for strategic planning systems (Rhyne 1985) and general cost management techniques (Cagwin and Bouwman 2002).

Whereas the number of customers in a firm's environment is a rather unambiguous variable, customer diversity/heterogeneity and customer interaction intricacy may have different meanings depending on which dimensions of the customer relationship are in scope. Two distinct dimensions can be identified: customer behavior and customer service requirements.

Customer behavior reflects the length, depth, and breadth of customer relationships (Bolton et al. 2004).

Hence, *customer behavioral complexity* can be defined as the degree of variation in retention durations (relationship length), transaction frequency and value of transactions (relationship depth), and cross-buying behavior (relationship breadth) across the total number of customer relationships a firm serves. The larger the variation in relationship length, depth, and breadth, and the larger a customer base firms serve, the higher customer behavioral complexity is faced by firms. Examples of industries with high customer behavioral complexity would be retailers and mass service providers such as telecommunication companies that serve very large and dynamic customer bases.

Customer behavior is not necessarily correlated with customers' service requirements. Resource consumption in marketing, sales, order-handling, distribution, technical service departments, customer support functions, etc. is caused by the amount and nature of activities performed to serve customers, and these activities may or may not be related to retention duration, transaction size, and cross buying behavior. Hence, *customer service complexity* is the degree of variation in service needs and requirements that invoke differential activities on an organization across customer-facing functions in terms of the number of activities performed as well as the time spent on each activity. The larger the variation in customers' service needs and requirements, and the larger a customer base a firm serves, the higher will customer service complexity be. Examples of industries with high customer service complexity would be manufacturers operating full supply chains and deploying large sales forces and/or large technical service forces.

Both customer behavioral complexity and customer service complexity should be measured through multi-item Likert scales. However, whereas customer service complexity can be measured as a first-order construct, customer behavioral complexity is best measured as a second-order construct consisting of three components: (1) variation in relationship length, (2) variation in relationship depth, (3) variation in relationship breadth. Table 3 provides a set of items for each of the two constructs.

The items for measuring customer behavioral complexity are examples of items that reflect the three conceptual components of customer behavior, which should increase construct validity. The items for measuring customer service complexity reflect the impact service complexity has on different elements in a firm's value chain ranging from pre-transaction activities (item 1) over activities related to the transaction (items 2–4) to post-transaction activities (item 5). This way all aspects of a firm's operations that are expectedly influenced by the service complexity encountered in customer environments are included in the measure. Marketing managers should be able to make an informed judgment regarding all of these items, which furthermore enhances the reliability of the measures.

Table 3 Likert scale items[a] for measuring customer behavioral complexity and customer service complexity

Customer Behavioral Complexity	
1.	Variation in relationship length
1.1	"In our markets customers switch between suppliers all the time."
1.2	"Some customers stay with our company for a long time while others prefer to shop around"
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."
2.2	"The variation in customer spending/use per transaction is large from transaction to transaction in our markets."
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."
3.2	"The variation in cross-buying across categories is large in our markets."
Customer Service Complexity	
1.	"Sales & marketing resource usage is different from customer to customer in our markets."
2.	"Core offerings (products/services) are customized to match the needs of individual customers in our markets."
3.	"Different customers are offered different commercial terms (i.e., price, rebates/discounts, credit terms etc.) in our markets."
4.	"Delivery/distribution resource requirements vary from customer to customer in our markets."
5.	"After-sale service resource requirements vary from customer to customer in our markets."

[a] Each of the scale items are measured as a 5-point scale ranging from Strongly Disagree (1) to Strongly Agree (5)

Framework and propositions

By linking up the two distinct customer complexity constructs with customer profitability measurement model sophistication we propose a contingency framework for customer profitability measurement model selection (see Fig. 1). The key notion is that firms will increase model sophistication only if the benefits of this increase outweigh the costs (Cooper 1988). Hence, in a customer environment characterized by low customer behavioral complexity and low customer service complexity the costs of implementing sophisticated CLV/CPA models are too high compared with the benefits that such measures produce. As complexity increases along the two dimensions of customer complexity the benefits of increasing sophistication will rise, which in turn will motivate firms to start implementing increasingly sophisticated customer profitability measurement models.

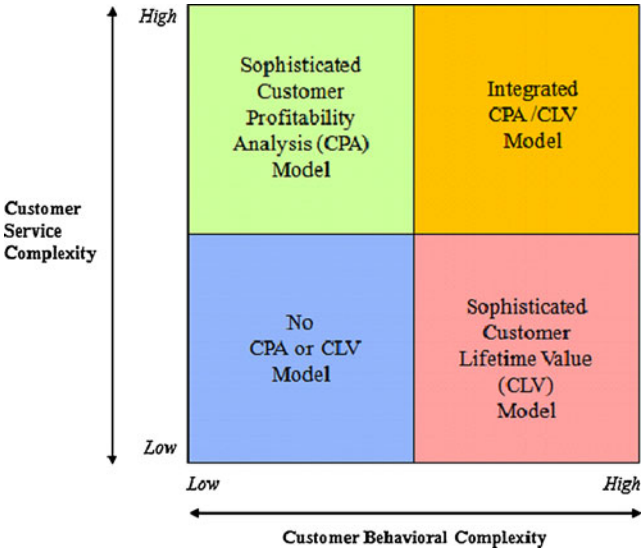

Fig. 1 A framework for customer profitability measurement model sophistication in environments characterized by different degrees of customer complexity

The framework for selecting a customer profitability measurement model that fits the complexity in the customer environment in which a firm operates has a range of implications for the kinds of sophisticated CLV/CPA models that will be advantageous to deploy. First, as service complexity increases, the differentiated demand for service activities across customer-facing functions leads to increasing variation in the share of service resource consumption that is to be attributed to different customers. The cost-differences that arise as a consequence of differentiated service levels can be substantial (e.g., Helgesen 2007; Niraj et al. 2001), which in turn yields a highly differentiated impact on firm net profitability across the customer base. Allocating resources according to customers' financial attractiveness in environments characterized by high service complexity therefore requires highly sophisticated CPA techniques. Higher degrees of sophistication are required to achieve better approximations of the resource consumption and the related costs associated with performing the heterogeneous range of customer service activities across all customer-facing functions. This leads to the first proposition:

P1: The greater customer service complexity an organization faces the more sophisticated CPA models will managers deploy when estimating customers' financial attractiveness.

Along the customer behavioral complexity dimension, increasingly diverse retention duration, purchase frequency, transaction size, and cross-buying behavior yield differential gross profit contribution from products/services across customers over time. Consequently, the evaluation of customers' financial attractiveness becomes a matter of understanding the profitability effects of individual customers' behavior over their lifetime. Therefore, the predictive, multi-periodic perspective on customer profitability embedded in sophisticated CLV models will be beneficial in environments characterized by high customer behavioral complexity as the key strength of these models is their ability to predict individual customer behavior in future periods and convert such predictions to a stream of expected gross customer cash flows. As customer behavioral complexity increases it will therefore be attractive for firms to adopt increasingly sophisticated CLV models. Hence, the second proposition:

P2: The greater customer behavioral complexity an organization faces the more sophisticated CLV models will managers deploy when estimating customers' financial attractiveness.

Failing to account for the diversity in service resource consumption encountered in customer environments characterized by high service complexity makes approximations of customers' financial attractiveness increasingly biased. This is because the total costs of serving the most demanding customers in such environments will generally be undervalued whereas the total costs of serving customers that draw less extensively on firm service resource capacity than the average customer will be overvalued. Consequently, customers that generate large gross profits by design receive preferential treatment even though they may potentially be causing significant service resource consumption which in turn makes these accounts unprofitable to serve. CLV models generally ignore service capacity resource consumption and derived cost-to-serve. Hence, deploying CLV models in customer environments characterized by high service complexity introduces bias to estimates of customers' financial attractiveness. All this leads to the third proposition:

P3: The greater customer service complexity an organization faces the larger bias will be introduced when managers use CLV models for estimating customers' financial attractiveness.

If firms neglect the time dimension when estimating customers' financial attractiveness in environments characterized by high behavioral complexity their estimates will ignore the differences in future gross profit potential across customers. Hence, by deploying single-periodic, retrospective customer profitability measurement models in such environments firms will undervalue customers that currently spend little money on the firm's offerings but that could potentially be turned into a loyal, frequent buyer across multiple categories. Similarly, the customers that currently generate high gross profits but have a high propensity to defect and/or can be expected to reduce their spending with the firm in the future will be overvalued in a single-periodic, retrospective customer profitability model. Subsequently, such customers will be allocated disproportionately high resource investments from the firm. Given CPA models' single-periodic nature these models will ignore customer dynamics in future periods and will therefore deliver increasingly biased estimates of customers' financial attractiveness as customer behavioral complexity increases. This takes us to the fourth proposition:

P4: The greater customer behavioral complexity an organization faces the larger bias will be introduced when managers use CPA models for estimating customers' financial attractiveness.

When operating in environments that are concurrently characterized by high customer service complexity and high customer behavioral complexity individual CLV and CPA models will not, if deployed in their current form, capture all dimensions of customers' financial attractiveness satisfactorily. Hence, the bias introduced by CLV (CPA) models in customer environments characterized by high service (behavioral) complexity will reduce the benefits of using even sophisticated CLV or CPA models in isolation. Such customer environments therefore call for an *integrated* customer profitability measurement approach where resource requirements and derived cost-to-serve are projected into the future. Sophisticated CLV techniques for estimating retention patterns, gross profits per transaction, and direct marketing costs must therefore be integrated with sophisticated CPA techniques for estimating the amount of service activities required to fulfill the future customer demands that the CLV technique predicts. This can be achieved by converting CLV estimates of future customer behavior into predicted service activity demands in future periods that, in turn, can be "translated" into cost estimates by utilizing the service activity cost drivers from the CPA technique. Only via this kind of integration will the customer profitability measurement model capture the full spectrum of customer relationship heterogeneities encountered in environments characterized by high customer service complexity and high customer behavioral complexity. Hence, the final proposition:

P5: In organizations that concurrently face high customer service complexity and high customer behavioral complexity managers will be more inclined to deploy integrated CPA/CLV models when estimating customers' financial attractiveness.

Future research implications

An important purpose of this article is to guide future research across the marketing and finance/accounting disciplines in establishing a more profound understanding of the contextual factors and boundaries affecting the sophistication of customer profitability measurement models. Three prolific avenues for future research can be identified: the propositions must be validated empirically, an integrated CLV/CPA approach must be developed, and the tax and risk limitations of CLV and CPA models must be explored and potentially diminished.

Validating the contingency propositions

A theory can be defined as "a statement of relationships between units observed or approximated in the empirical world" (Bacharach 1989, p. 498). Hence, the contingency propositions must be found to be irrefutable on the basis of empirical data in order to be validated. Whether adopting firms adapt the sophistication of customer profitability measurement models to fit the complexity of the customer environments in which they operate is one important issue. A key element herein is the confirmation that the constructs "customer service complexity" and "customer behavioral complexity" are valid empirical constructs. Cross-sectional survey research designs similar to the ones deployed in recent studies on the performance effects of CRM and customer prioritization strategies in general (see e.g., Homburg et al. 2008; Palmatier et al. 2006; Yim et al. 2004) constitute a good approach to testing the contingency propositions.

Another important issue is the exploration of bias introduced by CLV (CPA) models in customer environments characterized by high service (behavioral) complexity. Case demonstrations similar to the ones performed on CLV efficiency (e.g., Venkatesan and Kumar 2004) and CPA efficiency (e.g., Niraj et al. 2001) could be a good design for this kind of inquiry. Hereby, the diverging recommendations provided by CLV and CPA models can be analyzed, and the contingency explanation can be explored further.

Finally, other contingency factors than complexity may influence customer profitability measurement model sophistication. In their review studies of contingency research in management accounting, Otley (1980) and Chenhall (2003) identify six general contextual factors that may explain differences in the applicability of different accounting systems: "technology" (i.e., how the organization's work processes operate), "organization structure" (i.e., the formal specification of different roles to ensure that the organization's activities are carried out), "environment" (e.g., competitive intensity, uncertainty, turbulence etc.), "size," "strategy," and "culture." Future research can begin investigating the impact of some or all of these factors on the design of financial customer profitability models across companies. Subsequently, later studies can establish a more comprehensive contingency-based theory for customer profitability measurement model sophistication.

Developing an integrated CLV/CPA approach

Only one customer profitability measurement model study has explored the integration of the CLV and CPA approaches. Ryals (2005) touches upon the issue in a case study of a B2B insurer's implementation of a deterministic CLV model by assigning costs associated with order-handling and key account management activities to key accounts applying a variation of ABC. This is a promising (and pragmatic) approach. However, the link between customer behavioral forecasting and the prediction of service capacity costs (order-handling and key account management) was not explored.

Future research can explore this link in greater detail. A first step could be to pursue analytical research, investigating the relationship between the drivers of customer behavior deployed in CLV models and the cost drivers deployed in CPA models. In this context Activity-Based Budgeting (ABB) (Kaplan and Cooper 1998) and Time-Driven Activity-Based Costing (TDABC) (Kaplan and Anderson 2004) may be useful techniques to explore. Subsequently, case demonstrations similar to the ones carried out throughout the CLV and CPA literatures can be developed. This way a practically applicable integrated CLV/CPA model can be developed and demonstrated.

It is one thing to develop an integrated customer profitability measurement model. A more daunting task is to handle the issues associated with performing a successful implementation of such a model that offers benefits compelling enough for decision makers in firms to use it. Generally, barriers and resistance to change slow down the diffusion of management innovations (Ax and Bjørnenak 2005). In the case of customer profitability measurement models a key barrier to address is the cross-functional collaboration required across parts of the organization like marketing and finance/accounting departments (Kumar et al. 2008), departments that have traditionally been far apart (Gleaves et al. 2008).

Cross-functional collaboration presents two main issues. First, firms must successfully integrate cost management systems, transaction databases, CRM systems, other sales management software, etc. into an integrated customer profitability measurement platform that delivers insights on the drivers of customer value that are relevant to managers across different functions. For example, sales/marketing management must be able to monitor realized as well as expected gross profit per customer across offerings as well as the sales, marketing, and service activities performed to generate these gross cash flows. Additionally, simulation of different resource allocation strategies' effect on customer profitability in future periods must be facilitated. An important element herein is to organize data from operational customer service functions like order-handling, delivery, and post-transaction service/support around customers.

Second, processes and competences across functions must be aligned with the customer perspective while the overall customer responsibility is anchored in one function. This offers an opportunity for the marketing department to take lead on the entire organization's value creation process. As sales/marketing departments "own" the customer in most organizations, cross-functional customer or segment "account teams" are naturally headed by sales/marketing managers. Such account teams should consist of representatives from customer-related functions (e.g., R&D, logistics, customer service), with finance/accounting departments delivering data and controlling costs per customer. Sales/marketing managers should be in charge of account teams and overall responsible for customer/segment profitability. This kind of reorganization requires capability upgrades across all customer-related departments in order to adopt, implement, and use a common financial frame for resource allocation centered on customer profitability. Marketing managers in particular must achieve a much more in-depth understanding of the meaning of and interrelationships between accounting/finance terms. Similarly, accounting/finance managers need to understand the causal relationships between marketing actions and financial outcomes in much greater detail.

Understanding the process of breaking down such inter-functional barriers is a crucial step toward more rapid adoption of an integrated CLV/CPA model across companies. Longitudinal field studies may provide a good research design for exploring the issues associated with breaking down inter-functional barriers in one or more case companies that have adopted and implemented an integrated customer profitability measurement model (see Roslender and Hart 2003).

Expanding the boundaries of CLV/CPA

CLV- and CPA-based allocation of resources across multinational customer bases may suffer from the lack of an income tax perspective in CLV and CPA models. From a marketing perspective, tax considerations are part of the macro factors external to companies conducting global customer relationship management practices (Ramaseshan et al. 2006). Tax rate differentials may thus have an impact on optimization of resource allocation decisions in global CRM. If the effective tax rate varies across countries, customers with identical pre-tax cash flows do not necessarily contribute equally to firm value creation. On a similar note, different profit repatriation restrictions across countries may postpone the realization of after-tax cash flows across borders, thereby reducing net present value due to the time value of money. How severe a bias is introduced by ignoring tax discrepancies in multinational resource allocation and how any potential bias can be eliminated are interesting areas for future research. Again, case demonstrations comparing the resource allocation approach with and without tax considerations in a multinational marketing organization could be an interesting path to pursue.

The risk perspective of customer-based resource allocation decisions is to some extent captured in a CLV context by estimating the volatility and vulnerability of future customer cash flows (Kumar and Shah 2009). Although this approach is a major first step in accounting for diverse risk exposure across different customer relationships, there are still some issues that need to be addressed to advance this thinking.

According to financial portfolio theory, investors in financial markets can eliminate any asset-specific/idiosyncratic risk by holding a well-diversified portfolio of financial assets due to the inter-correlation of these assets' returns (Markowitz 1952). Transferring this logic to a customer portfolio yields two specific areas where the approach to measuring customer risk suggested by Kumar and Shah (2009) can be expanded: First, considering customer-level risk from a portfolio perspective rather than from the perspective of the individual customer will allow the incorporation of any diversification effects across the customer base. Dhar and Glazer (2003) have proposed a conceptual model for adjusting the cost of capital at the individual customer level to reflect different customers' contribution to the volatility of portfolio cash flows. Pursuing this model via case demonstrations would be an interesting way of exploring the impact of deploying a customer portfolio perspective on resource allocation decisions.

Second, a related issue is the reconciliation of customer-level risk to overall firm-level risk and the links between customer cash flow volatility/vulnerability and the weighted average cost of capital (WACC). Given that all sales activity derives from customer relationships, the risk differences estimated at the individual customer level provide an exciting micro-level approach to estimating firms' exposure to fluctuations in demand across markets at the macro level. Investigating how to merge this input into the overall estimation of the weighted average cost of capital of the firm will not only advance CLV models but may also provide new input to more macro-level estimation of firms' operational risk in corporate finance research.

Managerial implications

Customer profitability measurement model design is a matter of establishing the right fit between model sophistication and the complexity encountered in the customer environment. Customer complexity may vary across industries but may also vary across business units within organizations in specific industries. Hence, the determinants of customer complexity are not industry specific. Firms serving B2B as well as B2C customers (e.g., utilities, telecommunication firms, and financial institutions) may encounter differential customer behavior and service requirements so that firms must measure different elements of customers' financial attractiveness via more or less sophisticated measurement models. Similarly, firms that deploy different customer service models across different markets (e.g., by outsourcing service activities in some markets and being full-service provider in other markets) will face different degrees of customer service complexity.

Therefore, the first step in developing/adjusting customer profitability measurement models is to diagnose the customer environment across business units along the dimensions of customer service complexity and customer behavioral complexity. This diagnosis can be performed by surveying the sales/marketing organizations across business units using our proposed measures (see Table 3). Subsequently, firms can use the contingency framework to identify how sophisticated a CPA/CLV approach best fits this environment. Finally, firms must be aware of the limitations of CPA and CLV models in terms of the neglected tax effects and portfolio risk implications and mitigate the bias introduced to estimates of customers' financial attractiveness when developing resource allocation mechanisms wherever possible.

The next step is to develop/adjust the firm's customer profitability measurement model in accordance with the diagnosis of environmental customer complexity. Hence, when facing high degrees of customer service complexity a sophisticated cost assignment exercise must be performed. Efforts must therefore be made to approximate cause-and-effect relationships between customer service activities and service capacity resource requirements in order to determine cost-to-serve per customer. Similarly, firms facing high degrees of customer behavioral complexity must focus on performing sophisticated customer behavior forecasting analysis to estimate retention probabilities, gross profits, and direct marketing investments per customer. And if high degrees of service and behavioral complexity are encountered simultaneously an integrated CPA/CLV approach must be developed in a stepwise approach. First customers' service resource requirements and derived cost-to-serve can be determined. Then a model forecasting future customer behavior and direct marketing investment requirement should be developed. And finally the customer behavior forecasts can be used to estimate future customer service requirements, thereby arriving at a stream of net profits per customer that can be discounted to arrive at net value per customer.

A crucial final step is the implementation of the new/adjusted customer profitability measurement approach. In many cases this can potentially be a matter of shifting focus from a product perspective to a customer perspective across the organization (Kumar et al. 2008). Two important barriers to successful implementation include account manager motivation and feedback (Ryals 2006). Account managers must understand why customers are financially attractive or unattractive and how customers' financial attractiveness can be improved. This can be done by focusing on the drivers of CPA (service activity time consumption and derived resource requirements) and CLV (retention probabilities, depth and breadth of engagements, and direct marketing investment requirements) rather than by merely managing on financial customer outcomes. This also entails the measurement of account manager performance on the drivers they can influence. Relevant examples of elements that account managers can influence are pricing, the product mix that customers purchase (over time), marketing budgets at customer level, time spent on sales calls, and other service levels that account managers "promise" customers in terms of, e.g., promotion support, deliveries, and after-sale support. Examples of elements that are beyond account managers' influence are efficiencies in production (reflected in cost of goods sold per unit), logistics, and technical service (reflected in cost-to-serve). However, the implementation of sophisticated customer profitability measurement models is still an important step in highlighting customer service processes that can be optimized internally in firms.

Conclusion

No customer profitability measurement approach is universally superior. Instead firms must balance the degree of CPA and CLV sophistication with the customer service complexity and customer behavioral complexity encountered in their task environment. How sophisticated CPA and CLV models can be developed has been demonstrated a number of times in isolation. How the two approaches can be integrated into a unified model is an underdeveloped area that deserves attention in future research on customer profitability measurement. Future research of this nature requires interdisciplinary collaboration between marketing and management accounting scholars just as well as the implementation of sophisticated CPA and CLV models across firms requires higher degrees of inter-functional coordination across marketing/sales and finance/accounting departments.

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