



Discussion Paper

Customer Lifetime Network Value

by

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Abstract

Today, people are increasingly connected and extensively interact with each other using technology-enabled media. Hence, customers are more frequently exposed to social influence of other customers when making purchase decisions. However, established approaches for customer valuation most widely neglect network effects based on social influence leading to a misallocation of resources. Therefore, following a design-oriented approach, this paper develops a model for customer valuation referred to as the customer lifetime network value (CLNV) incorporating an integrated network perspective. By considering the net network contribution of customers, the CLNV reallocates values between customers based on social influence without changing the overall network value, that is, a firm's customer equity. Using a real-world dataset of a European online social network, we demonstrate and evaluate the applicability of the CLNV. We show that the CLNV enables a sound determination of both individual customers' value and firm's customer equity and supports thorough customer segmentation.

Keywords: Customer valuation, customer lifetime value, customer relationship management, social influence, network effects

Introduction

“We went from a connected world to a hyperconnected world” (Friedman 2013). For instance, nowadays people are increasingly connected and extensively interact with each other using technology-enabled media. Thus, extensive word-of-mouth (WOM) is generated by the rising number of connected customers (e.g. via Facebook or Twitter) and dispersed with previously unknown reach, intensity, and speed. Customers heavily rely on such WOM generated by other customers when searching for information about products or services (Moon et al. 2010) or help in purchasing decisions (Chen and Xie 2008). In fact, 84% of customers indicate that WOM influences their purchase decisions (Nielsen 2013). This remarkable importance of customer-to-customer interactions has been intensively discussed in prior research (cf. e.g. Algesheimer and Wangenheim 2006; Libai et al. 2013; McAlexander et al. 2002). With respect to customer valuation, it is consequently crucial not to evaluate customers isolated from each other but in a network context. For instance, think of customers who did not purchase anything but whose social influence induced purchases of several other customers. When neglecting network effects, such customers would be valued as unprofitable and ignored when making strategic customer decisions (e.g. targeted marketing), although these customers did in fact add value to the company.

Even though research has dealt extensively with customer valuation (e.g. Berger and Nasr 1998; Blattberg and Deighton 1996; Dwyer 1997), network effects in customer valuation have not been extensively investigated yet. Only very few studies started to address selected aspects of network effects in general customer valuation models (e.g. Domingos and Richardson 2001; Hogan et al. 2003). Also, as regards one of the most well-known customer valuation models, the customer lifetime value (CLV), research has considered social influence only rarely. Most of the existing approaches concentrate on including the network effect incentivized through marketing campaigns by compensating referrals with a higher customer value (e.g. Kumar et al. 2007; 2010c; Lee et al. 2006; Libai et al. 2013). Further studies extend the CLV and the customer referral value by a third component that considers network aspects arising outside of incentivized referral campaigns and seeding programs (e.g. Kumar et al. 2010b; Weinberg and Berger 2011). However, to the best of our knowledge, none of the studies considers the mirror-inverted effect yet: customers may also “owe” value to the network due to the social influence of other customers on their cash flows. Hence, existing models are subject to double counting, as the additional value component representing the network effects is once considered for the customer inducing other customers’ cash flows and once for the customers actually generating these cash flows. Thus, existing models overestimate the overall value of the customer base, that is, firm’s customer equity (CE).

Therefore, following a design-oriented approach (cf. Hevner et al. 2004) the aim of this paper is to develop a model for customer valuation incorporating an integrated network perspective, in the following referred to as the customer lifetime network value (CLNV). The basic idea of the CLNV is to reallocate values between customers based on network effects without changing the overall network value. To do so, we determine the value of a customer based on the *present value of the individual cash flows* generated by him or her and the *present value of his/her net value contribution to the network*. We demonstrate the applicability and relevance of the CLNV using a real-world case of a European online social network (OSN) focusing on sports. This demonstration is an essential part of the Design Science research process (cf. Gregor and Hevner 2013; Hevner et al. 2004; Peffers et al. 2007). Access to data both on user interactions and on the purchase behavior of users gives us the rare opportunity to research network effects in the context of customer valuation using real-world data. Overall, the CLNV contributes to research and practice in three ways: First, it enables a well-founded valuation of individual customers incorporating an integrated network perspective; second, it facilitates a sound determination of a company’s CE as the sum of all customers’ CLNV; and third, it supports thorough customer segmentation. Thus, we also contribute to the IS literature, particularly by two means: First, we add to the growing body of IS literature on technically enabled networks (for an overview cf. e.g. Berger et al. 2014; Heidemann et al. 2012a; Probst et al. 2013) by designing a novel approach for customer valuation, the CLNV, which extends existing metrics and allows to account for IS enabled changes in customer behavior. Second, we add to IS literature focusing on the assessment of IS investments related to customer values (such as CRM investments, cf. e.g. Heidemann et al. 2012b; Zablah et al. 2012) by raising further awareness for the role of social influence among customers and suggesting the CLNV as a potential metric that allows for considering such network effects.

The remainder of this paper is organized as follows: In the next section, we briefly review the theoretical foundations and related literature. We then develop the CLNV model as a new customer valuation method integrating the network perspective. Next, the applicability of the CLNV is demonstrated by using a real-world case of a European OSN focusing on sports. Thereby, we also discuss the CLNV in comparison to the classic CLV and show how a novel customer segmentation based on the CLNV can be applied. Finally, we conclude with a summary of our contribution and a discussion of limitations and options for further research.

Literature Background

Customer Networks and Social Influence

Based on technology-enabled media, people are increasingly connected and extensively interact with each other. Against this background, companies face the situation that customers can no longer be regarded as more or less isolated individual customers. Rather, customers are parts of (digital) social networks that strongly influence each other and their purchase decisions across personal and regional boundaries. Similar to social networks in general (cf. Adamic and Adar 2003; Bampo et al. 2008; Wassermann and Faust 1994) such customer networks can formally be represented by a graph consisting of a set of nodes (representing the customers) and a set of edges (representing the influence between pairs of customers).

Various studies (for an overview cf. Probst et al. 2013) reveal that social influence in social networks can change the “belief, attitude, or behavior of a person” (Erchul and Raven 1997, p. 138), including their purchase decisions (cf. e.g. Algesheimer and Wangenheim 2006; Amblee and Bui 2012; Gross and Acquisti 2005; Weinberg and Berger 2011). Social influence can be induced through different forms of interactions, such as one-to-one or one-to-many WOM, observation respectively imitation, and information sharing (Arndt 1967; Herr et al. 1991; Iyengar et al. 2011b; Kumar et al. 2010b; Libai et al. 2013; Nitzan and Libai 2011; Wangenheim and Bayón 2007). The resulting effect is often also referred to as “social contagion” and can have five reasons (cf. e.g. Hinz et al. 2014; Iyengar et al. 2011b; Van den Bulte and Wuyts 2007): First, information transferred in interactions may increase the awareness of and interest for a topic such as a product (cf. e.g. Katz and Lazarsfeld 1955). Second, information about costs and benefits of actions reduces search efforts and uncertainty and therefore increases adaption (cf. e.g. Iyengar et al. 2011a). Third, normative pressure to fulfill the expectations of others (cf. e.g. Asch 1951), or fourth, imminence of real status and competitive disadvantages can induce a change in behavior. Fifth, network externalities can increase the consumption of goods. These externalities imply that with every additional customer consuming a good the value of consuming this particular good increases (cf. e.g. Granovetter 1978; Katz and Shapiro 1994).

Prior research showed that social influence is of high relevance for companies: On the one hand, connections between customers can be used for referrals. Hence, social influence between customers can help companies to acquire new customers at relatively low acquisition costs (Kumar et al. 2007, 2010c; Lee et al. 2006). Villanueva et al. (2008) and Schmitt et al. (2011) even found that in the long term customers acquired through customer referrals are more profitable for a company than customers acquired through traditional marketing. On the other hand, social influence between customers can affect the purchase decisions and the loyalty of existing customers (Kumar et al. 2010b; Nitzan and Libai 2011; Weinberg and Berger 2011). Consequently, companies increasingly try to actively manage customers’ interactions by identifying and targeting those customers with large influence on other customers, so-called influencers (Bampo et al. 2008; Goldenberg et al. 2009; Heidemann et al. 2010; Hinz et al. 2011; Trusov et al. 2010). Recent research has highlighted that, in addition to customer characteristics such as age, gender, education, and expertise (Aral and Walker 2012; Eccleston and Griseri 2008; Gladwell 2000; Katona et al. 2011; Valck et al. 2009; Watts and Dodds 2007; Zhang et al. 2010; 2011), the structure of the network, in particular its edges, can affect a customer’s influence on other customers. In this context, a customer’s connectivity, for example his or her number of indirect connections, is shown to affect a customer’s influential power (Algesheimer and Wangenheim 2006; Ganley and Lampe 2009; Goldenberg et al. 2009; Hinz et al. 2011; Kiss and Bichler 2008; Nitzan and Libai 2011). Additionally, as inactive connections do not imply information exchange or social influence, customers’ communication activities or interactions are increasingly used to identify influencers (Cheung and Lee 2010; Heidemann et al. 2010; Oestreicher-Singer and Zalmanson 2009; Valck et al. 2009; Xu et al. 2008).

In this paper, we argue that it is essential to not only identify and target influencers but to likewise consider their social influence in customer valuation. Thus, in the presence of social influence within customer networks, a customer's value should not only consider the cash flows directly generated by him or her (e.g. through purchases) but also the network effects in terms of his or her social influence on the cash flows of others customers in the network (e.g. through referrals) and vice versa.

Customer Valuation and Network Effects

Customer valuation per se is of high practical relevance and has been subject of extensive prior research (cf. e.g. Berger and Nasr 1998; Blattberg and Deighton 1996; Kotler and Armstrong 1996). The classic CLV constitutes one of the most well-known customer valuation models and is widely accepted in research and practice. The CLV is defined as the sum of a customer's discounted present and expected future cash flows (Berger and Nasr 1998). Hence, it considers the profit (revenue minus costs) a company is expecting to earn with a customer over his or her lifetime by selling and servicing to him or her. The CLV and its various adaptations, for example, the retention model and the migration model (Dwyer 1997), have proven useful in a variety of contexts such as prioritizing and selecting customers, optimizing the timing of product offerings, evaluating competitor companies, or supporting merger and acquisition decisions (cf. e.g. Kumar et al. 2004; Kumar et al. 2008; Venkatesan and Kumar 2004).

However, recent studies have shown that it is essential to explicitly consider network effects in the context of customer valuation. Against this background, a few authors started to address selected aspects of network effects in general customer valuation models (cf. e.g. Domingos and Richardson 2001; Hogan et al. 2003). Hogan et al. (2003), for instance, determine network effects when accessing the value of a lost customer using the Bass new product growth model. They argue that a company that loses a customer does not only lose his or her future cash flows but also the cash flows of other customers due to slower customer acquisition caused by reduced social influence. Another example is the work of Domingos and Richardson (2001) who model a Markov random field and distinguish two components: the customer's intrinsic value representing the value s/he generates via direct purchases, and the customer's network value representing the value s/he generates via social influence on other customers.

Also with respect to the CLV, prior research has considered selected aspects of network effects (Kumar et al. 2007; 2010b; 2010c; Lee et al. 2006; Libai et al. 2013; Weinberg and Berger 2011). When valuating a customer, these studies consider the original cash flows generated by a particular customer (as in the classic CLV) and add a so-called "customer referral value", which covers cash flows of other customers that have been induced by him or her through a referral that is incentivized through specific marketing campaigns (Kumar et al. 2007, 2010c; Lee et al. 2006; Libai et al. 2013). Lee et al. (2006), for instance, consider a customer's original cash flows (as in the classic CLV) and the savings in acquisition costs of new customers obtained through that customer's social influence. Kumar et al. (2007, 2010c) add the net present value of all future cash flows of the customers who would not have joined the company without the referral to the referring customer's value. Using field experiments, they show that both components of the customer value, the classic CLV and the customer referral value, are not necessarily positively related and some customers with a low CLV and a high customer referral value are as valuable as others with solely a high CLV. They consequently argue that assessing customers without integrating their network value leads to a systematic underestimation in customer valuation. Libai et al. (2013) focus on network effects in WOM-seeding programs. In contrast to previous research, they do not aim at assessing network effects for individual customers, but determine the value of entire WOM-seeding programs using agent-based modeling. Taken together, these approaches concentrate on including the network effect incentivized through marketing campaigns by compensating referrals with a higher customer value.

Further studies extend the CLV and the customer referral value by a third component that considers network aspects arising outside of incentivized referral campaigns and seeding programs (Kumar et al. 2010b; Weinberg and Berger 2011). This allows for a generalization to non-campaign contexts. For instance, Kumar et al. (2010b) introduce the "customer influencer value" as a third value component. While campaign-based effects are covered by the customer referral value, the customer influencer value comprises all network effects that are not formally incentivized by a company, for instance, effects occurring due to regular user interaction in social media. Kumar et al. (2010b) quantify the customer influencer value based on a customer's number of connections, his or her strength of ties ("weak links with several groups are expected to have a higher customer influencer value because they are more

effective in spreading a message than customers who have strong links with a smaller set of groups”), and the “emotional valence” of the customer’s interactions (cf. Kumar et al. 2010b, p. 302). Similarly, Weinberg and Berger (2011) define the total value of a customer, referred to as the “connected customer lifetime value”, as the sum of the CLV, the customer referral value and the “customer social media value”. While Kumar et al. (2010b) include all non-incentivized effects in the customer influencer value, Weinberg and Berger (2011) only include social media based non-incentivized effects in the customer social media value. The customer social media value is therefore modeled as a multiplication of the CLV and multiple factors representing the impact of social media, for instance, a customer’s engagement level in a specific social media channel (e.g. Facebook, Twitter) and this channel’s influential power. The latter can for example be modeled as a function of a channel’s durability of information (e.g. in Twitter information can disappear from the screen within seconds while in blogs information remains available for months) and its depth respectively richness of information (e.g. OSN like Facebook have diverse users and therefore enable a more differentiated discussion). According to Weinberg and Berger (2011), the resulting customer social media value is at no time negative.

Summing up, particularly in the context of the CLV previous studies started to consider selected aspects of network effects in customer valuation. They recognized that customer valuation models should not solely consider the original cash flows directly generated by a customer when purchasing products or services. Rather, the customer value should also consider that a customer’s social influence may have an effect on the cash flows of other customers in the network. To do so, previous work suggested adding further value components to the classic CLV representing the value of company incentivized referrals or positive effects of exerted social influence in the customer network.

Research Gap and Contribution to Research

While existing studies included the relevance of customers with high influence on other customers in customer valuation, they did not consider the mirror-inverted effect yet: customers may also “owe” value to the network due to the social influence of other customers on their cash flows. Hence, existing models are subject to errors and double counting, as the additional value component representing the network effects is once considered for the customer inducing other customers’ cash flows and once for the customers actually generating these cash flows. As a result, existing valuation models overestimate the overall value of the customer base of a company (i.e. the company’s CE), leading to a misallocation of resources. In fact, several studies have acknowledged that their approaches cause double counting (Kumar et al. 2010b; 2010c; Weinberg and Berger 2011). Kumar et al. (2010b, p. 308), for example, recognize that “[...] although CLV and Customer Referral Value involve separate metrics, they cannot be added up across all customers”. If a company’s CE is calculated based on these models, it is admitted “[...] that the sum of all customers’ CCLV [connected customer lifetime values] is greater than the sum of all customers’ CLV” (Weinberg and Berger 2011, p. 342).

Against this backdrop, following a design-oriented approach (cf. Hevner et al. 2004) we aim at developing a novel customer valuation model considering network effects due to social influence in a well-founded way, avoiding the problem of double counting. We take an integrated network perspective and refer to our model as the CLNV. Thus, we substantially extend existing work by not only adding additional value components but also detracting value from customers if their cash flows are mainly based on the influence of other customers in the network. We thereby acknowledge the fact that while parts of the cash flows in customer networks would not occur without the social influence of other customers, they would not occur either without the customers actually generating them when purchasing products or services. Taken together, our paper contributes to the existing body of knowledge in customer valuation in three ways: (1) the CLNV enables a well-founded valuation of individual customers considering network effects (avoiding an overestimation of customers whose cash flows mainly depend on the influence of other customers) (2) the CLNV enables a sound determination of a company’s CE as the sum of all customers’ CLNV (avoiding the problem of double counting and the overestimation of a company’s customer base); and (3) the CLNV splits network effects occurring in customer networks, enabling to reward exerting social influence as well as actual purchasing behavior resulting in cash flows. Thus, we also contribute to the IS literature, particularly by two means: First, technically enabled networks such as Online Social Networks and their effects on customer behavior have become an intensively researched IS topic over the last 10 years (cf. e.g. Berger et al. 2014; Heidemann et al. 2012a; Probst et al. 2013). Prior IS research emphasized the necessity to reflect on IS induced changes such as today’s role of online customer-to-customer interactions (cf. e.g.

Libai et al. 2010) and to adapt existing metrics such as the CLV accordingly: “[r]esearch needs to establish metrics that reflect changes in business activities that have some degree of permanence” (Straub et al. 2002, p. 118). Our work adds to the growing body of IS literature on technically enabled networks by designing a novel approach for customer valuation, the CLNV, which extends existing metrics and allows to account for IS enabled changes in customer behavior. Second, customer valuation metrics such as the CLV and the CE can be used to assess the outcome of IS investments, for instance, when building customer-centric information systems (cf. e.g. Liang and Tanniru 2007), determining the scope of CRM systems (cf. e.g. Heidemann et al. 2012b), or investigating performance implications of CRM technology use (cf. e.g. Zablah et al. 2012). As social influence might considerably influence the value of customers, neglecting networks effects when applying established customer valuation metrics such as the CLV could lead to wrong design decisions or bias empirical studies. Thus, we add to IS literature focusing on the assessment of IS investments related to customer values by raising further awareness for the role of social influence when using customer value metrics in IS research and by suggesting a potential metric, the CLNV, that allows to account for social influence among customers when assessing the outcome of IS investments related to customer values.

Modeling Customer Lifetime Network Value

Setting and Basic Idea

We consider a company and a network of customers. The network can be represented by a set of nodes representing customers and a set of directed and weighted edges representing the strength of influence between pairs of customers (e.g. induced by WOM spread in messages between customers) (cf. e.g. Adamic and Adar 2003; Bampo et al. 2008; Heidemann et al. 2010; Hinz et al. 2011). Each customer in the network can generate cash flows. The existence and amount of a specific customer’s cash flows may depend on the influence of other customers in the network (e.g. through WOM). To manage its customer portfolio, the company quantifies the value of each customer based on the cash flows generated.

We introduce the following example to illustrate the setting: Consider a network with three customers 1, 2, and 3 (cf. Figure 1). The amount of cash flows generated by these customers is represented by the size of the circles. The customers’ influence on each other is represented by arrows between the customers. The direction of the arrows represents the direction of the influence; the size of the arrows represents the strength of the influence.

Due to the influence of customers 2 and 3, parts of the cash flows of customer 1 may depend on these customers. Thus, the value of customer 1 would be overestimated when just looking at the cash flows generated directly by him or her. This is due to the fact that a share of these cash flows might not have been generated without the influence of customers 2 and 3. In contrast, the cash flows of customer 3 do not depend on other customers. However, customer 3 might highly influence the cash flows of customer 2 and even more those of customer 1. Hence, the value of customer 3 within this network might be higher than what the cash flows directly generated by him or her suggest. Taken together, this rather straight forward example already shows that accounting for the influence of customers on each other is crucial, as ignoring such network effects when deciding “which customer to market to can lead to severely suboptimal decisions” (Domingos and Richardson 2001, p. 57).

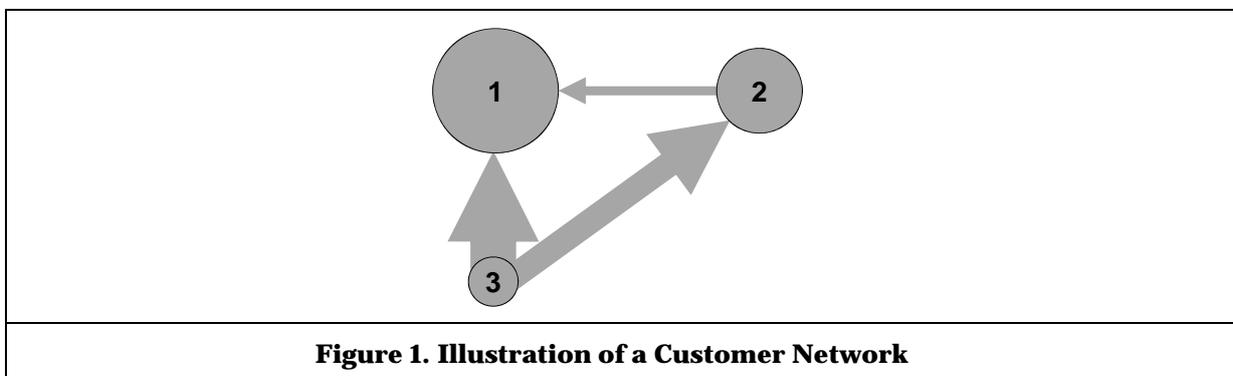


Figure 1. Illustration of a Customer Network

We investigate the problem of valuating and segmenting customers in the presence of network effects induced by the influence among customers. As outlined above, focusing solely on the cash flows directly generated by a customer, as for instance the classic CLV does (cf. e.g. Berger and Nasr 1998), primarily leads to an underestimation of customers that induce a share of other customers' cash flows by exerting influence on them (cf. customer 3 in Figure 1) (Domingos and Richardson 2001; Hogan et al. 2003; Weinberg and Berger 2011) and an overestimation of customers whose cash flows (or a share of them) can be traced back to the influence of other customers (cf. customer 1 in Figure 1).

As the starting point for our CLNV model, we assume the structure of the customer network (i.e. the number of nodes and edges including the direction and weight of the latter) and each customer's cash flows as given. To calculate the *CLNV*, we now determine the value of a customer based on the *individual cash flows* generated by him or her (as in the classic CLV) and a network component representing his or her net contribution to the network, referred to as Δ *network contribution*:

$$CLNV = \text{present value of individual cash flows} + \text{present value of } \Delta \text{ network contribution}$$

Previous studies have started to include network effects in customer valuation by increasing the value of a customer who induces the cash flows of other customers (e.g. Kumar et al. 2007; 2010b; 2010c; Libai et al. 2013; Weinberg and Berger 2011). We build on these existing approaches and propose to also decrease the value of a customer if his or her cash flows have been partly induced by the influence of other customers (cf. Oestreicher-Singer et al. 2013). In contrast to existing research on network effects in customer valuation, our network component, Δ *network contribution*, can consequently be both positive and negative, depending on the influence or susceptibility of the respective customer. Overall, three outcomes are possible:

1. Customers who show more cash flows due to their influence on other customers' cash flows than they "owe" cash flows to the network due to the influence of other customers on their own cash flows (positive Δ *network contribution*) will be valued higher than for instance in the classic CLV (cf. customer 3 in our example).
2. Customers who "owe" more cash flows to the network due to the influence of other customers on their own cash flows than they show cash flows due to their influence on other customers' cash flows (negative Δ *network contribution*) will be valued less than for instance in the classic CLV (cf. customer 1 in our example).
3. The valuation of customers with no or balanced network effects (Δ *network contribution* = 0) will be the same as for instance in the classic CLV.

As a consequence, the sum as well as the present value of all cash flows generated by the network of customers does not change. Hence, we overcome one of the major unresolved challenges when valuating customers in the presence of network effects (cf. literature review in the previous section). In the following, we present our CLNV model in detail.

The Customer Lifetime Network Value Model

Along the lines of the classic CLV, we define the CLNV as the present value of the current and expected future cash flows $CF_{i,t}^{CLNV}$, where $i = 1, \dots, N$ denotes the customer and $t = 1, \dots, T$ the time period the cash flow occurs in. T represents the expected lifetime of the customer relationship. Cash flows are discounted with a discount rate d . With this notation, the $CLNV_i$ of a customer i can be expressed as follows:

$$CLNV_i = \sum_{t=0}^T \frac{CF_{i,t}^{CLNV}}{(1+d)^t}, \quad (1)$$

where $CF_{i,t}^{CLNV} \in \mathfrak{R}$ denotes the cash flows that are assigned to customer i in period t (including Δ *network contribution*), and
 $d \in \mathfrak{R}^+$ the discount rate.

As outlined above, we expand the classic CLV by including network effects. Building on previous works (e.g. Domingos and Richardson 2001; Weinberg and Berger 2011), we define the cash flows $CF_{i,t}^{CLNV}$ as the sum of the expected cash flows $CF_{i,t}$ generated by a customer i in period t (as in the classic CLV) and a

network component $\Delta CF_{i,t}^{network}$. In line with the classic CLV the cash flows $CF_{i,t}$ are defined as the customer's revenues minus the respective costs including for instance costs of acquiring, maintaining, selling, servicing, and marketing the customer (Singh and Jain 2013). As indicated above, our network component significantly differs from existing research. Instead of solely including the effect a customer has on the network (e.g. induced by referrals to other customers), we consistently consider the effect the network has on the customer (e.g. induced by referrals of other customers). We define $\Delta CF_{i,t}^{network}$ to represent the Δ network contribution of customer i considering both, cash flows of other customers induced by the influence of customer i as well as customer i 's cash flows that are induced by the influence of other customers. Based on this notation, $CF_{i,t}^{CLNV}$ can be expressed as follows:

$$CF_{i,t}^{CLNV} = CF_{i,t} + \Delta CF_{i,t}^{network}, \quad (2)$$

where $CF_{i,t} \in \mathfrak{R}$ denotes the cash flows generated by customer i in period t , and

$\Delta CF_{i,t}^{network} \in \mathfrak{R}$ customer i 's Δ network contribution in period t , measuring the net contribution of customer i to the network.

The net contribution of customer i to the network, $\Delta CF_{i,t}^{network}$, consists of two components. The first component, referred to as $CF_{i,t}^{influence}$, considers all cash flows of other customers in the network that are induced by the influence of customer i . The second one, denoted as $CF_{i,t}^{influenced}$, considers the share of customer i 's cash flows that are induced by the influence of other customers in the network. A further difference to the existing literature on customer valuation in networks (e.g. Kumar et al. 2007; 2010b; 2010c; Lee et al. 2006; Libai et al. 2013; Weinberg and Berger 2011) is that we do not ascribe the cash flows entirely to the customers inducing them. We rather introduce a weighting factor that represents how a company assesses the importance of inducing cash flows through the influence on other customers versus generating cash flows oneself which have, however, been induced by the influence of other customers. Hence, we ascribe the share α of $CF_{i,t}^{influence}$ to customer i recognizing that without his or her influence inducing these cash flows they would not have occurred. Inversely, the share $(1-\alpha)$ of $CF_{i,t}^{influence}$ remains with the customers generating the cash flows, recognizing that without their final purchase decisions the cash flows would not have occurred either. Along the same lines, we subtract the share α of $CF_{i,t}^{influenced}$ from customer i and ascribe it to the customers inducing it with their influence, leaving customer i with the share $(1-\alpha)$. Please note that as discussed above, the net contribution of customer i to the network, $\Delta CF_{i,t}^{network}$, can still be positive, negative, or zero. We define $\Delta CF_{i,t}^{network}$ as:

$$\Delta CF_{i,t}^{network} = \alpha CF_{i,t}^{influence} - \alpha CF_{i,t}^{influenced}, \quad (3)$$

where $\alpha \in [0,1]$ denotes the weighting factor appointed by the company,

$CF_{i,t}^{influence} \in \mathfrak{R}$ the cash flows of other customers induced by the influence of customer i in period t , and

$CF_{i,t}^{influenced} \in \mathfrak{R}$ the cash flow of customer i induced by the influence of other customers in period t .

We now define $CF_{i,t}^{influence}$ as the sum over the cash flows generated by all other customers j that have been influenced by customer i in period t . The set of customers j being influenced by customer i is referred to as $Influenced(i, t)$ in the following. We denote the strength of customer i 's influence on a customer j 's cash flows in period t as $s_i^{t \rightarrow j}$. Obviously, influence does not always result in cash flows. The probability that being exposed to the influence of others results in actual purchases, in the following referred to as conversion rate, correlates with several personal and social factors (cf. Katz 1957; Weimann 1991). In this context, for example the strength of the connection between the influencer and the customer being influenced (Algesheimer and Wangenheim 2006; Nitzan and Libai 2011), the personal characteristics of the influencer, and the influencer's competence regarding the product or service under consideration play an important role (Eccleston and Griseri 2008; Gladwell 2000; Watts and Dodds 2007). In the following, the probability that influence exerted by customer i actually induces a customer j 's cash flows in period t is referred to as $c_i^{t \rightarrow j}$. Finally, $CF_{i,t}^{influence}$ depends on the average cash flows generated by customer j in

period t , which we approximate by the average gross contribution of customer j in period t ($p_{j,t}$). Thus $CF_{i,t}^{influence}$ can be expressed as follows:¹

$$CF_{i,t}^{influence} = \sum_{j \in Influenced(i,t)} s_t^{i \rightarrow j} \cdot c_t^{i \rightarrow j} \cdot p_{j,t}, \quad (4)$$

where $Influenced(i, t)$ denotes the set of customers j that are influenced by customer i in period t ,

$s_t^{i \rightarrow j} \in \mathfrak{R}_0$ the strength of influence exerted by customer i on customer j in period t ,

$c_t^{i \rightarrow j} \in [0,1]$ the conversion rate representing the probability that influence exerted by i on j actually leads to a purchase of customer j in period t , and

$p_{j,t} \in \mathfrak{R}_0$ the average gross contribution of customer j in period t .

Along the same lines, we define $CF_{i,t}^{influenced}$ as:

$$CF_{i,t}^{influenced} = \sum_{j \in Influence(i,t)} s_t^{j \rightarrow i} \cdot c_t^{j \rightarrow i} \cdot p_{i,t}, \quad (5)$$

where $Influence(i, t)$ denotes the set of customers j that exert influence on customer i in period t ,

$s_t^{j \rightarrow i} \in \mathfrak{R}_0$ the strength of influence exerted by customer j on customer i in period t ,

$c_t^{j \rightarrow i} \in [0,1]$ the conversion rate representing the probability that influence exerted by j on i actually leads to a purchase of customer i in period t , and

$p_{i,t} \in \mathfrak{R}_0$ the average gross contribution of customer i in period t .

Finally, we can define the $CLNV_i$ of a customer i as follows:

$$CLNV_i = \sum_{t=0}^T \frac{CF_{i,t} + \alpha \sum_{j \in Influenced(i,t)} [s_t^{i \rightarrow j} \cdot c_t^{i \rightarrow j} \cdot p_{j,t}] - \alpha \sum_{j \in Influence(i,t)} [s_t^{j \rightarrow i} \cdot c_t^{j \rightarrow i} \cdot p_{i,t}]}{(1+d)^t}. \quad (6)$$

In the following, we illustrate the calculation of the CLNV using the example introduced above.

An Illustrative Example

Consider Figure 2 in which the network from above is supplemented by further information on cash flows, $CF_{i,t}$, the strength of influence, $s_t^{i \rightarrow j}$, the conversion rate, $c_t^{i \rightarrow j}$, and the average gross contribution, $p_{i,t}$. We assume a time horizon of one period ($T = 1$), a discount rate of 10% ($d = 0.1$), and a weighting factor of 50% ($\alpha = 0.5$). The results are presented in Table 1.

In a first step, $CF_{i,t}^{influence}$ and $CF_{i,t}^{influenced}$ are calculated using Equations 4 and 5. For example, $CF_{3,1}^{influence}$ of customer 3 in $t = 1$ can be calculated as follows: $CF_{3,1}^{influence} = 50 \times 20\% \times 10\text{€} + 10 \times 10\% \times 15\text{€} = 115\text{€}$. $CF_{3,1}^{influenced}$ yields 0€, as customer 3 is not influenced by any other customer. For customer 2, however, $CF_{2,1}^{influenced} = 2 \times 50\% \times 10\text{€} = 10\text{€}$.

In a second step, we calculate the net contribution $\Delta CF_{i,t}^{network}$ of each customer i to the network by using Equation 3. For example, the net contribution of customer 3 to the network is $\Delta CF_{3,1}^{network} = 0.5 \times 115\text{€} - 0.5 \times 0\text{€} = 57.5\text{€}$.

Finally, the $CLNV$ can be calculated using Equation 6. For customer 3, this results in $CLNV_3 = (20\text{€} + 0.5 \times 115\text{€} - 0.5 \times 0\text{€}) / (1 + 0.1)^1 = 77.5\text{€} / 1.1^1 = 70.5\text{€}$. Table 1 summarizes the results for all three customers in the example.

¹ It is generally possible to define influence, conversion rates, and average order values as product specific variables. For reasons of simplicity and practicability, we refrain from this differentiation at this point.

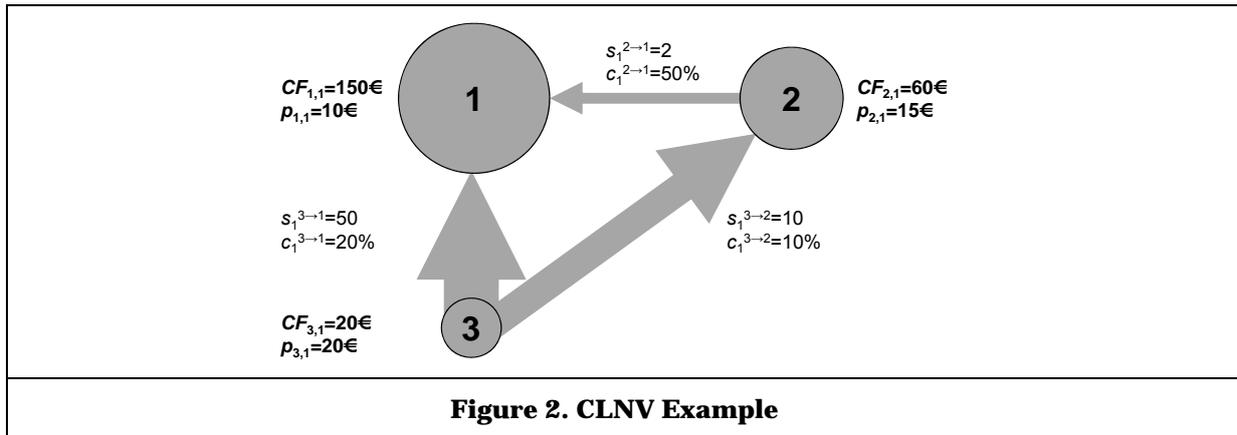


Table 1 highlights that customer 3 has a positive net contribution to the network, while customer 1 has a highly negative one and customer 2 a slightly negative one. To further interpret the results, we compare them with the classic CLV of 136.4€ for customer 1, 54.5€ for customer 2, and 18.2€ for customer 3. While customer 3 is not influenced by other customers in the network, customer 1 “owes” a share of his or her cash flows to the network. Consequently, for customer 1 the CLNV is substantially lower than the classic CLV while for customer 3 the CLNV is substantially higher. For customer 2, the CLNV and the classic CLV are almost identical, as the cash flows of other customers induced by the influence of customer 2 and the cash flows that customer 2 “owes” to the network due to the influence of customer 3 are also almost identical. Remembering that the basic idea of our model is to reallocate cash flows without, however, changing the overall value of the network, we check the sum over the $CLNV_i$ and the CLV_i for all three customers: indeed, both yield 209.1€.

	Customer 1	Customer 2	Customer 3
CF_i [€]	150.0	60.0	20.0
$\Delta CF_{i, network}$ [€]	-55.0	-2.5	57.5
$CF_i^{influence}$ [€]	0.0	10.0	115.0
$CF_i^{influenced}$ [€]	110.0	15.0	0
CF_i^{CLNV} [€]	95.0	57.5	77.5
$CLNV_i$ [€]	86.4	52.3	70.4

Demonstration and Evaluation

In the following, as an essential part of the Design Science research process (cf. Gregor and Hevner 2013; Hevner et al. 2004; Peffer et al. 2007), we demonstrate and evaluate the applicability of our CLNV model using a real-world dataset of a European OSN focusing on sports. First, we introduce the general setting and the dataset, and motivate the relevance of the CLNV in the context of this OSN. Second, we operationalize the input parameters for the CLNV based on historic data and apply it to the present context. Third, we evaluate the applicability by discussing the key findings of the application of the CLNV and the derived customer segmentation.

Setting and Dataset

The European OSN focusing on sports was founded in 2007. It was initially designed as a pure OSN for active and passive (e.g. fans) sportsmen interested in socializing and communicating about sports related topics like fitness, nutrition, or health. For instance, users discuss current sports events like the soccer world cup qualification or compare workout plans. The OSN provides users with basic functions to

socialize and interact with each other (i.e. creating user profiles, managing contacts, and sending messages) comparable to other OSN. One major difference, however, to OSN such as Facebook is that the OSN did not have a public “wall” at the time of our investigation. Thus, all interaction among users took place in public discussion forums or privately via messages. Public discussion forums were only marginally used and did not contain relevant interactions between customers. In fact, no significant interactions besides private messages were observed. In 2009, the OSN started an affiliated online shop on a pilot basis selling sports products. The shop was intended as a supplementary area of engagement and as an additional source of revenue besides advertising revenues. During the time frame under consideration, the shop offered selected sports products with attractive discounts (e.g. hiking backpacks or blood pressure meters) exclusively to members of the OSN.

In order to successfully launch and advertise the affiliated shop, the OSN planned to run user specific targeted marketing campaigns. To do so, key users were supposed to be identified, segmented, and addressed based on customer values. The OSN emphasized that besides actual customers purchasing products users who were actively involved in the OSN and recommended products to other users were also expected to be valuable for the shop. These users were supposed to help the OSN to increase the number of customers by leveraging their influence on other users’ purchase decisions. Hence, the classic CLV was not adequate for the required customer valuation, since it values customers isolated from each other neglecting that users can influence purchases of other users. Instead we agreed to consider network effects by using our CLNV model. Indeed, the OSN and its affiliated shop provided an optimal setting to apply the CLNV model in a real-world case. Having access to both data on user interactions in the OSN and on their actual purchase behavior gave us the rare opportunity to integrate network effects based on influence among (potential) customers into customer valuation. Please note that the focus of the following application is on the revenues from the affiliated online shop only, we do not consider revenues from additional sources such as advertising.

In our application, we use two datasets including interaction and purchasing data of the OSN and its affiliated shop spanning a nine-month period between July 2009 and March 2010. Consider Table 2 for a description of the datasets. The first dataset includes all users of the OSN and all messages exchanged among these users in the relevant period including information on the sender, the recipient, and the time stamp. This dataset contains 60,029 users. Overall, 264,020 messages were sent by 5,902 of these users in the period under investigation, on average 44.7 messages per user. The low share of users sending messages is typical for networks such as OSN and has also been found in prior research (e.g. Benevenuto et al. 2009; Wilson et al. 2009). All of the 60,029 users received at least one message, on average 4.4 messages per user. The second dataset contains information about the users purchasing products in the online shop, including the date of the purchases and the corresponding gross contributions. In total, 650 purchases were made by 497 of the 60,029 users (respectively customers). Naturally, the minimum amount of purchases of these users was 1, the maximum amount of purchases per user was 8. The average gross contribution of a customer’s purchase was 49.5 €, with a maximum of 390 €.

Incidence	Respective users (% of all users)	Totals	Mean per respective user
Messages (sent)	5,902 (9.8 %)	264,020.0	44.7
Messages (received)	60,029 (100.0 %)	264,020.0	4.4
Purchases	497 (0.8 %)	650.0	1.3
Gross contribution [€]	497 (0.8 %)	24,577.9	49.5

Application of the Customer Lifetime Network Value

To apply the CLNV, in a first step all input parameters had to be operationalized based on the available data. To guarantee a reasonable and practicable application, we based our operationalization on both previous research and the discussions with the operators of the OSN.

Determination of the time period t and the expected lifetime of the customer relationship T . We decided to use monthly time periods. Such sub-annual time periods are adequate for the fast-moving, dynamic environment of OSN and enable a differentiated view on changes in user behavior. This is consistent with previous research (e.g. Kumar et al. 2007). In addition, monthly time periods acknowledge the fact that the affiliated shop had just been launched and marketing campaigns to promote the shop were required to be designed and implemented promptly. To determine the expected lifetime T of customer relationships, previous research often uses hazard rate models forecasting the probability of defection or purchase (cf. e.g. Helsen and Schmittlein 1993; Jain and Vilcassim 1991). In our application drawing on historic data, we were able to determine each customer's lifetime of the customer relationship based on his or her historic transaction data.

Determination of the discount rate d . Discount rates strongly depend on the specific situation and risks of a company. Therefore, we based our estimation on discussions with the operators of the OSN and the affiliated shop. As a result, the monthly discount rate was set to $d = 0.008$. This is equivalent to an annual discount rate of 10% used by the OSN in similar contexts in the past. Furthermore, an annual discount rate of 10% is consistent with previous research of customer valuation in the context of networks and marketing (cf. e.g. Libai et al. 2012; Weinberg and Berger 2011).

Determination of the weighting factor α . In general, the weighting factor determines the importance a company attaches to a user inducing cash flows through his or her influence on other (potential) customers versus actually generating cash flows herself or himself. A weighting factor of $\alpha = 0$ implies that a company does not value a customer's influence inducing cash flows at all. For instance, companies assuming that customers purchase their products independently of social influence would choose a weighting factor of 0. In that case, the results of the CLNV would coincide with the classic CLV. In contrast, a weighting factor of $\alpha = 1$ implies that companies do not value a customer's final decision to purchase but solely the social influence of other users inducing his or her purchases. Companies assuming that purchases would not occur without social influence would choose a weighting factor close to 1. In case of the OSN under investigation, we set the weighting factor to $\alpha = 0.5$ to reflect that the OSN rated the importance of inducing cash flows through social influence and actually generating cash flows equally.

Determination of the strength of influence $s_i^{i \rightarrow j}$. Literature widely agrees upon the fact that users in OSN influence other users through social interactions such as messages (e.g. Cheung and Lee 2010; Ganley and Lampe 2009; Garg et al. 2011; Hinz et al. 2011; Oestreicher-Singer and Zalmanson 2009; Shriver et al. 2013). As previously discussed, in addition to customer characteristics such as age, gender, education, and expertise, the impact of social influence strongly depends on the strength of the connections among users, which can be determined by the number of interactions (Chun et al. 2008; Heidemann et al. 2010; Kiss and Bichler 2008; Xiang et al. 2010). In our application, we focused on the number of messages s /he sent to other users ($s_i^{i \rightarrow j}$) to represent a user's strength of influence. Conversely, the strength of influence other users have on him or her was estimated using the number of messages s /he received ($s_i^{i \leftarrow j}$). This acknowledges that in the context of the OSN investigated private messages are the primary means of communication. Moreover, we found that the number of messages and purchases are indeed positively and significantly (for a significance level of 0.01) correlated, thus affirming our operationalization of the strength of influence. The fact that not every message is related to products offered in the affiliated shop, and thus a source of influence, is covered by the conversion rate defined below. In case of our sports OSN no significant interactions besides private messages were observed and thus no other interactions besides private messages were considered when determining the strength of influence ($s_i^{i \rightarrow j}$). However, in other contexts where significant interactions besides private messages occur and may influence customers' purchase behavior, these should be considered analogously. For public discussion forums, for instance, the strength of influence ($s_i^{i \rightarrow j}$) can be determined based on the number of posts (sent and received) instead of the number of messages (sent and received). However, when considering different forms of interactions, these have to be assessed regarding their influence potential. For example, in public discussion forums one post may reach various recipients, but the strength of influence of such a post on a single recipient may significantly differ from the strength of influence of a private message personally addressing him or her.

Determination of the cash flows $CF_{i,t}$ and the gross contributions $p_{i,t}$. Usually, the concept of the CLV and also our CLNV are forward looking and require a prediction of future cash flows. However, for our demonstration and evaluation we use historic transaction data as proxy drawing on existing

approaches in the literature using the customers' historic purchasing behavior as well. Previous research has in fact found historic data on revenues and costs to be good predictors for future revenues and costs (cf. Kumar et al. 2010c). Thus, we determined each user's monthly cash flows ($CF_{i,t}$) based on his or her aggregated monthly gross contributions ($p_{i,t}$). If a user made more than one purchase in a month, the average monthly gross contribution ($p_{i,t}$) was calculated by dividing the sum of all purchases' gross contributions in the corresponding month by the number of purchases the user made in that period. There are also studies raising the question whether historic behavior is a very accurate predictor for future behavior (cf. e.g. Jain and Singh 2002; Malthouse and Blattberg 2005). As in our paper we do not focus on developing a new method to predict customers' future revenues or costs but propose a generally new customer valuation model and show its applicability, we chose a simple backward looking perspective using historic purchasing data. For future research and application in other contexts we suggest to include customer-level factors when forecasting revenues and costs, for instance customer demographics, product usage variables (e.g. product categories), marketing activities, and costs of switching to other companies (e.g. Jain and Singh 2002; Singh and Jain 2013).

Determination of the conversion rate $c_i^{i \rightarrow j}$. The conversion rate ($c_i^{i \rightarrow j}$), representing the probability that a message sent by i on j leads to a purchase of user j , was operationalized based on two components:

$$c_i^{i \rightarrow j} = \frac{s^{i \rightarrow j}(\text{purchase}_j)}{s^{i \rightarrow j}} \cdot \frac{o_t(s_t^{i \rightarrow j})}{s_t^{i \rightarrow j}(\text{purchase}_j)} \quad (7)$$

The first component of Equation 7 represents the share of user i 's messages that are relevant to purchases of user j . Thus, if for instance the number of user i 's overall messages to user j ($s^{i \rightarrow j}$) is relatively small but the number of his or her messages relevant to a purchase of user j ($s^{i \rightarrow j}(\text{purchase}_j)$) is relatively high, the conversion rate of user i is relatively high. Note, that we do not expect a user to have the same share with all users but assume that the share depends on the strength of each relationship (cf. e.g. Barrat et al. 2004; Brown and Reingen 1987; Burt 1992; Granovetter 1973). Therefore, the first component in Equation 7 varies depending on both the sender and the receiver of messages. Furthermore, we assume that the relationship between users i and j does not change considerably over our 9-month observation period. Hence, the first component is expected to be constant over time. We approximated $s^{i \rightarrow j}(\text{purchase}_j)$ by analyzing the chronology of messages and purchases. To account for the fast-moving nature of online interactions, we assumed that only if purchases were generated within a 10-day period after receiving a message, this message could be considered as relevant for the purchase. The second component represents a correction term measuring the number of induced purchases of user j ($s_t^{i \rightarrow j}(\text{purchase}_j)$) per purchase-relevant message that s/he receives ($o_t(s_t^{i \rightarrow j})$). Hence, it accounts for cases in which one purchase-relevant message induces more than one purchase or one purchase is induced by more than one purchase-relevant message. The term thus measures the efficiency of purchase-relevant messages sent to user j in time period t . The correction term can be equal to one or larger or smaller than one. If it equals one, one message induces one purchase. If it is larger than one, one message induces more than one purchase. If it is smaller than one, more than one message was sent to induce one purchase – either by one or by various users. In the latter case, the influence on user j was equally split between those users.²

Calculation of the CLNV. Finally, after having operationalized all parameters, we calculated the CLNV for each user as the sum of the *present value of individual cash flows* and the *present value of Δ network contribution*. For all 601 users with a positive CLNV, Table 3 gives an overview of the average CLNV as well as the CLNV's main components. On average, the *present value of individual cash flows* accounted for 28.4 €. Due to the design of our model, the average present value of Δ network contribution was 0 €, as the two opposing components, $CF_{i,t}^{\text{influence}}$ and $CF_{i,t}^{\text{influenced}}$, balanced each other. However, the *present value of Δ network contribution* varied substantially between -55.0 € (-31% of the *present value of the individual cash flows* of the particular user) and 233.9 € (336% of the *present value of the individual cash flows* of the particular user). Most of the variance resulted from the variance of users influencing other users ($CF_{i,t}^{\text{influenced}}$). Taking all components together, the average $CLNV_i$ accounted for 28.4 €, with a

² Note that an alternative way of operationalizing the conversion rate would be to estimate it using a multivariate regression model (cf. e.g. Goh et al. 2013; Shriver et al. 2013). Because of limited data availability due to the shop being in its ramp up phase we refrain from such an estimation of the conversion rate in context of our application.

minimum of 0.09 € and a maximum of 309.4 €. Thus, as designed in the model, the average CLNV coincides with the present value of *individual cash flows*: the CLNV reallocates cash flows but does not change the overall value of the network. Overall, 601 users had a positive $CLNV_i$ and therefore a positive value for the affiliated shop of the OSN. These are 20.9% more users than the 497 customers that actually purchased products in the period under investigation.

Customer specific variable	Mean	Minimum	Maximum	Standard deviation
<i>Present value of individual cash flows</i> [€]	28.4	0.0	309.4	33.8
<i>Present value of Δ network contribution</i> [€]	0.0	-55.0	233.9	14.4
<i>Present value of $CF_{i,t}^{influence}$</i> [€]	3.6	0.0	527.1	28.0
<i>Present value of $CF_{i,t}^{influenced}$</i> [€]	3.6	0.0	110.0	11.1
$CLNV_i$ [€]	28.4	0.09	309.4	34.3

Key Findings of the Application and Discussion of the Results

Discussion of the Findings of the CLNV in Comparison to the classic CLV

First, we compare the value of each user measured by the CLNV with the value s/he had with respect to the classic CLV. 104 users did not generate cash flows by purchasing products. Consequently, these users would not have been considered when focusing only on actual customers who purchased at least one product on their own (cf. classic CLV). For further 116 users the CLNV and the classic CLV differed as well. Overall, 36.6% of all 601 users with positive CLNV would have been misvalued when ignoring network effects and using the classic CLV. Hence, even our setting with the shop being in its ramp up phase demonstrates dramatically how important it is to consider network effects in customer valuation. Otherwise managers are very likely to misallocate a significant share of resources, for instance, when designing targeted marketing campaigns.

Second, taking a more detailed look on the results, we observe both an overvaluation and an undervaluation of users by the classic CLV. 18.5% of all 601 users were substantially overvalued when using the classic CLV. This is due to the fact that a share of customers' cash flows might have not been generated without the influence of other users leading to a negative Δ network contribution. Hence, companies in general, or in our case the OSN, might spend too many resources on such customers when ignoring network effects. For 18.1% of all 601 users in our application, the classic CLV accounted for less than the CLNV. This is the case if customers have a positive Δ network contribution (0.8% of all 601 users) or if users do not generate cash flows by buying products on their own (and would thus not have been considered when focusing solely on customers) but have a positive Δ network contribution (17.3% of all 601 users). Such users would be undervalued when ignoring network effects. Most of them (104 out of 111), that is, more than 15% of all 601 users with positive CLNV, would even be completely ignored in marketing campaigns based on the classic CLV. While these users did not make purchases in the affiliated shop on their own, they still are highly valuable for the OSN as their influence is very likely to induce cash flows of other customers.

Third, the sums of the CLNV and CLV, both being 17,057.2 €, do not differ. Hence, the application of the CLNV altered the allocation of value among users compared to the classic CLV, but did not change the overall value of the OSN measured by the sum of customer values. Thus, our CLNV model overcomes one of the major shortcomings of existing approaches (cf. literature review).

Taken together, we argue that it is very important to include network effects into customer valuation, as it is possible by applying our CLNV model. By not just basing the value of a user on the individual cash flows generated by him or her but also on his or her net contribution to the network, the CLNV advances the classic CLV and helps to better allocate resources such as marketing budgets.

Novel Customer Segmentation Based on the CLNV

As outlined above, the operators of the OSN intended to use the CLNV to design targeted marketing campaigns and improve advertising for the affiliated shop. Therefore, the CLNV has been used to differentiate distinct user segments as depicted in Figure 3 (cf. also Kumar et al. 2007).

As segmentation criteria we used the CLNV's two main components *present value of individual cash flows* and *present value of Δ network contribution* (cf. Figure 3). The first criterion was subdivided into the two degrees *high* and *low*, split by the median of the present value of individual cash flows. The second criterion was subdivided into the three degrees *negative*, *zero*, and *positive* with respect to the *present value of Δ network contribution*. The three user segments that scored *high* on the criterion *present value of individual cash flows* were named *Champions* and the ones scoring *low* *Misers* (cf. Kumar et al. 2007). Depending on the score of the second criterion, we referred to the *Champions* as *Influencing Champions* (i.e. users with positive Δ network contribution), *Classic Champions* (i.e. users with zero Δ network contribution), and *Influenced Champions* (i.e. users with negative Δ network contribution). Accordingly, we differentiated the segments that scored *low* on the first criterion as *Influencing Misers*, *Classic Misers*, and *Influenced Misers*. The size of the segments and their average CLNV are presented in Figure 3.

We can draw two main findings from Figure 3: First, in our application the average CLNV varies substantially between the six segments, starting with the *Influencing Champions* with 122.8 € and ending with the *Influencing Miser* with 7.8 €. Note that the low value of the latter can be explained by their average individual cash flows being close to 0 €. Their value almost solely results from influencing other customers. Second, the distribution of users across the six segments varies considerably. Fairly no users (0.5%) perform well on both criteria, thus being classified as *Influencing Champions*. 32.1% of all users were segmented as *Influenced Champions* or *Influencing Misers*, while most of the users belong to the *Classic Champions* and *Classic Misers* showing no network effects. Thus, we identified substantial potential to improve users' value, by moving users from *Misers* to *Champions* and by moving users from *Classic* and *Influenced* users to *Influencing* users.

Present value of individual cash flows	HIGH	Influenced Champions 14.5% of all users Average CLNV = 40.4€	Classic Champions 33.0% of all users Average CLNV = 48.3€	Influencing Champions 0.5% of all users Average CLNV = 122.8€
	LOW	Influenced Misers 4.0% of all users Average CLNV = 10.2€	Classic Misers 30.4% of all users Average CLNV = 13.9€	Influencing Misers 17.6% of all users Average CLNV = 7.8€
		NEGATIVE	ZERO	POSITIVE
		<i>Present value of Δ network contribution</i>		

Figure 3. CLNV-based User Segments (n = 601)

Based on this customer segmentation, we designed a marketing campaign. Thereby, we determined the reasonable investment for each user by comparing his or her present CLNV with the intended CLNV. For illustration, selected marketing efforts for each segment are briefly sketched in the following.

Classic Champions and Influenced Champions. To turn *Classic Champions* and *Influenced Champions* into *Influencing Champions*, these users can be encouraged to actively recommend products they bought to other users. In this context, vouchers based on the number of induced purchases as

monetary incentives complemented by e-mails including a link proposing to “recommend today” could be used. While e-mails to *Classic Champions* can help to promote the OSN in general, e-mails to *Influenced Champions* could refer to their positive experience with recommendations of friends.

Influencing Misers. To increase the *present value of individual cash flows* of *Influencing Misers* vouchers for individual purchases in the affiliated shop could be offered. For example, users could receive vouchers for the products, which have been bought by other users as result of their recommendation, as reward for their social influence. Such vouchers could be complemented by an e-mail thanking for recommending the shop’s product to other users. Without the CLNV, the OSN would have classified those users as invaluable and would not have made the required investment to target them.

Influenced and Classic Misers. *Influenced* and *Classic Misers* could be monetarily incentivized for both purchasing products and using their influence to induce other users to purchase in the OSN’s affiliated shop. Thus, such users could be targeted by combining both marketing actions described above.

Conclusion on Contribution, Limitations, and Further Research

Contribution to Research and Practice

In this paper we developed a model for customer valuation incorporating an integrated network perspective, referred to as the CLNV. The CLNV determines the value of a customer based on the *present value of the individual cash flows* generated by him or her through purchases and a network component reflecting the *present value of his/her net value contribution to the network*. Thus, existing customer valuation models are substantially extended not only by adding an additional value component but also detracting value from a customer if his or her cash flows are mainly based on social influence. Consequently, the CLNV reallocates values between customers based on network effects without changing the overall value of the network. The applicability of the CLNV model was demonstrated and evaluated using a real-world dataset of a European OSN focusing on sports. Our contribution to theory and practice is threefold:

First, the CLNV enables a well-founded valuation of individual customers: By taking an integrated network perspective that considers mirror-imaged network effects both for customers influencing other customers and customers that are influenced, the CLNV ensures a correct individual valuation of all customers in two ways. First, in contrast to the classic CLV, customers without individual purchases who induce cash flows of other customers by their social influence are valued positively. Based on the classic CLV, these customers would have a value of zero or negative. Second, by decreasing the value of a customer if his or her cash flows are induced by the influence of other customers, the customer’s value is assessed adequately and is not overestimated as in the classic CLV (e.g. Berger and Nasr 1998) and in previous models considering network aspects (e.g. Kumar et al. 2007; 2010c; Weinberg and Berger 2011). Both effects are crucial for decision makers when deciding whom to market to: On the one hand, without the CLNV customers who would increase profits of a company will be ignored in campaigns. On the other hand, the CLNV helps companies to avoid marketing to unprofitable customers.

Second, the CLNV enables a sound determination of a company’s CE: Our model is the first to contain network effects and at the same time to ensure a determination of a company’s CE by aggregating individual customer values like the classic CLV. Key to this is our integrated network perspective ensuring that network effects are not double counted. In contrast, previous models tend to overestimate the company’s CE as they count induced values twice, once for the customer whose social influence induces purchases and once for the customer generating them. They are forced to calculate CE based solely on the classic CLV: only “[...] keeping CLV and CRV separate ensures that ‘double counting’ of cash flows is avoided” (Weinberg and Berger 2011, p. 332). Hence, when assessing a company’s CE, decision makers should use the CLNV to avoid wrong strategic decisions, for instance, in mergers and acquisitions.

Third, the CLNV enables well-founded customer segmentation: Based on the CLNV’s two main components, that is, *present value of individual cash flows* and *present value of Δ network contribution*, customer segments can be identified. This segmentation extends both the informative content of segmentation based on the classic CLV (only using the present value of individual cash flows) and the segmentation based on previous models considering network effects (not accounting for negative net network contributions). Thus, the segmentation based on the CLNV may help companies to design better

customized marketing campaigns: Customers with low present value of individual cash flows should be incentivized to buy more, for instance, by vouchers for individual purchases, customers with low Δ network contribution should be incentivized to influence other customers, for instance, by vouchers depending on the number of recommendations a customer makes.

Limitations and Further Research

Besides the highlighted contribution, our model it is also subject to limitations. First, not every company has sufficient data to track the influencing behavior of customers (cf. Kumar et al. 2010c), which is a common limitation of novel models. However, our application, likewise based on basic data, shows how limited data availability on social influence can be overcome by approximating parameters. For instance, we used the number of messages as a proxy for the strength of influence. Indeed, companies may even have further information that can be used to improve the measurement of social influence and the conversion rate. For instance, data on user demographics could be used to complement the determination of the conversion rate. Second, we have to recognize endogeneity issues as the common challenges to the study of social networks (e.g. Manski 2000). Thus, network effects may be lower than estimated in our application. We addressed this issue by making conservative assumptions about the chronology of messages and purchases. Third, we demonstrated and evaluated the applicability of our CLNV model using one single dataset of an OSN in the context of sports. Nevertheless, while we see a validation of our model for further cases as desirable, we argue that the results drawn from our case may be generalized to other OSN for three major reasons: (1) The sports network we investigated shows the typical characteristics of OSN. In fact, the sports OSN provides users with basic functions to socialize and interact with each other comparable to other OSN like Facebook and LinkedIn (i.e., creating user profiles, managing contacts, and sending messages) (cf. Boyd and Ellison 2007; Heidemann et al. 2012a). (2) The sports OSN is comparable to other OSN in regard to the demographics of their users. For instance, similar to social media platforms like Facebook, My Space, and Instagram, the average age of users in the sports OSN is slightly below 30 years (cf. Caverlee and Webb 2008; Duggan et al. 2013). (3) The products sold in the sports OSN's affiliated online shop are products in the context of sports, however coming from a variety of product categories. For example, in the investigated time period the shop sold hiking supplies, like backpacks and tents, sports equipment like heart rate watches, and sports apparel. We see this variety of products as an additional argument for the generalizability of the results from our case.

Besides these limitations, we see two promising starting points for future research. First, we focused on positive network effects so far not including the effect of potential negative social influence (c.f. e.g. Weinberg and Berger 2011). On the one hand, it is possible to include negative influence originating from negative reviews into Δ network contribution by means of a negative gross contribution $p_{j,t}$ (cf. Equation 4). Thus, for the customer inducing the negative influence, $CF_{i,t}^{influence}$ and therefore his or her CLNV will be decreased. On the other hand, it is possible to allow for negative strength of influence $s_i^{-\gamma}$ in the case messages contain negative reviews (cf. Equation 4). Analogous to the first solution this decreases the CLNV of the customer inducing the negative influence. A major challenge when considering negative reviews respectively negative WOM is to measure negative social influence, in particular assessing whether a purchase would have occurred without the presence of negative WOM. This could be done either by surveying customers or simulating customer behavior (cf. e.g. Hogan et al. 2003; Kumar et al. 2007; 2010c) or by categorizing messages using text mining techniques (cf. e.g. Gamon et al. 2005; Hu and Lui 2004; Pang et al. 2008). Second, we focused on social influence on present customers assuming the customer network to be stable. Including growth of customer networks into valuation can be an interesting journey for further research. For instance, the rate of admittance of new customers could be simplified by a projection of a compound annual growth rate. However, in the long run this does not seem reasonable as the growth of OSN dampens over time. Thus, we propose to build a projection model considering the underlying network structure, as done in previous research in the context of OSN (e.g. Mislove et al. 2008; Kumar et al. 2010a).

We hope that our paper contributes to a better understanding of customer valuation in the context of customer networks and stimulates further research by serving as starting point for future work.

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