Customers' Influence Makes or Breaks Your Brand's Success Story – Accounting for Positive and Negative Social Influence in Online Customer Networks

Completed Research Paper

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Abstract

The ongoing proliferation of digital technologies is reshaping the customer-firm relationship by providing new possibilities for companies and customers to interact with each other. Companies try to involve customers in firm-sponsored online customer networks to connect them more deeply with the brand. In this context, the impact of positive social influence induced among customers on their value contribution has been acknowledged, however, research often neglects the impact of negative social influence. We propose therefore a novel approach to account for direct and indirect as well as positive and negative social influence between customers in online customer networks to calculate customers' integrated value contribution. We demonstrate the applicability of our approach using an illustrative online customer network. Our approach allows practitioners to evaluate customers' "true" value in online customer networks by preventing over- and underestimation of customers' value contribution.

Keywords: Social Influence, Online Customer Network, Customer Valuation

Introduction

The worldwide proliferation of social technologies facilitated and enhanced the rapid dissemination of information and individuals' opinions. As a consequence, the opportunity to transmit information to much larger online networks emerged (Hennig-Thurau et al. 2004). In the course of this development, customers' role changed from a traditionally more passive role towards active creation and publishing of information, emotions, and opinions (Roberts and Dinger 2016). Based on this evolution, it is not surprising that customers' purchase decisions are increasingly driven by their social influence on each other. For example, Hill et al. (2006) discovered an up to four times higher favoritism of a new product if customers had previously interacted with an early adopter of this product. Similarly, Kumar et al. (2013) showed that social influence disseminated in online networks significantly contributes to growth in sales, stimulates positive

Word-of-Mouth, and spreads brand knowledge. Respectively, numerous researchers have demonstrated that social influence plays a paramount role in customers' decision making processes (e.g., Adjei et al. 2010; Amblee and Bui 2011; Scholz et al. 2013).

Acknowledging the growing importance of social influence in online networks, companies have recognized the benefits of engaging customers directly via firm-specific online networks. Online customer networks represent specialized, non-geographically bound firm-sponsored online communities whose members are interested in the firm's products, services, or topics and perform different forms of social engagement to interact with each other (McAlexander et al. 2002; Muniz and O'Guinn 2001). Thus, with rising popularity, many companies started to engage their customers directly through online customer networks. According to Manchanda et al. (2015), to date, up to 50% of the top 100 global companies like *Disney*, *Procter & Gamble,* or *Amazon* host their own online customer network. Thereby, the relevance of online customer networks for customers and the motivation for customers to participate in such networks are manifold (e.g., Dholakia et al. 2004; Zaglia 2013). Often, customers join online customer networks to seek advice, specifically tailored to their product interests and needs, because online customer networks enable them to engage with like-minded customers which are perceived as more trustworthy or respectable (Wu et al. 2010). Besides advice seeking, learning and improving their skills within a particular area of expertise is another main reason for customers to join online customer networks (Dholakia et al. 2004). In turn, online customer networks are relevant for companies as they offer the opportunity to gain a competitive advantage: Recent research has shown that online customer networks provide an excellent opportunity to increase customers' brand awareness, generate positive Word-of-Mouth, magnify trust, and amplify brand loyalty (e.g., Barreda et al. 2015; Dessart et al. 2015; Nadeem et al. 2015; Wang et al. 2016). In fact, several studies suggest a positive link between customers' engagement in online customer networks and customers' loyalty and/or profitability (e.g., Felgenhauer et al. 2017; Islam and Rahman 2017; Pihl 2013).

To benefit from this form of customer engagement, it is fundamental for companies to understand the impact of customers' social influence on each other's purchase behavior within online customer networks. Against this background, researchers started to analyze individuals' social influence, for example, to identify influential users (e.g., Goldenberg et al. 2009; Heidemann et al. 2010; Kiss and Bichler 2008) and to distinguish between more or less valuable customers in respect to their influential effect on other customers' purchase decisions (e.g., Däs et al. 2017; Nejad et al. 2014). However, investigating a customer's social influence solely based on answering the question "how much influence does this individual exert on others?" disregards the integration of the answer to the question "what kind of influence, positive or negative, does this individual exert on others?". Both, researchers and practitioners, agree that negative social influence induced by one customer towards another results in loss of business value (Arndt 1967; Däs et al. 2017; Kumar et al. 2010a; Weinberg and Berger 2011). In fact, multiple studies observed a noticeable differential effect between positive and negative social influence on customers' purchasing behavior and decision making processes (e.g., Ballantine and Au Yeung 2015; Floh et al. 2013; Lee et al. 2008). Therefore, positive and negative social influence cannot be treated as having the same effect on customers' purchase behavior when accounting for social influence in online customer networks. Ma et al. (2008) pointed out that previous models mostly neglect the presence of negative social influence in online customer networks and are therefore not distinguishing between the economic effect of positive and negative social influence on other customers' purchase behavior (e.g., Ho et al. 2012; Libai et al. 2013). So far, only few models attempted to incorporate negative social influence in their concepts (e.g., Deffuant et al. 2005; Kumar et al. 2013).

Thus, the aim of this paper is to propose an approach to determine customers' value contribution by accounting for positive as well as negative social influence in online customer networks. Our approach focuses on the fact that there is significant difference between customers who exert negative social influence and customers who exert positive social influence on other customers. Overall, our approach contributes to research and practice in three ways: First, we enable a well-founded valuation of customers' value contribution by accounting beside positive also for negative social influence among customers; second, we consider both direct and indirect social influence spreading virally through an online customer network; and third, we reallocate individual customer's value contribution by avoiding double counting of value contribution at the same time. We therefore allow a suitable evaluation of a company's customer equity based on the individual customers' integrated value contribution in the online customer network. The applicability of our approach is demonstrated by means of an illustrative online customer network.

The remainder of this paper is organized as follows: In the next section, we review the theoretical foundations and the related literature. We then develop a novel approach to account for positive and negative social influence in online customer networks. Thereafter, we demonstrate the applicability of our approach, followed by a discussion of implications for theory and practice as well as critical reflection on limitations and options for future research. Finally, we conclude with a brief summary of our results.

Theoretical Background

The Role of Social Influence in Online Customer Networks

Social influence is described as people's attitudes, beliefs, and opinions influencing each other's decision making processes (Liang et al. 2011; Venkatesh and Morris 2000) based on "the transmission of various pieces of information among people who are connected to one another" (Nitzan and Libai 2011). Thereby, Word-of-Mouth (WoM), both in an offline and online context (eWoM) describes the transmission of information between customers who exert positive or negative influence on each other's purchase decisions (Nitzan and Libai 2011). However, social influence in a digitally connected world, i.e. eWoM, differs from traditional WoM, as it connects a variety of individual users by extending each customer's finite offline network to a sheer infinite world of Internet users (Cheung et al. 2009; Dellarocas 2003). Hence, eWoM is more voluminous in quantity and consists of multiple sources of information readily available for consumers (Chatterjee 2001). Social technologies further fuel the growing significance of social influence by offering new ways and greater variety of opportunities for customers to engage with each other. Customers express and spread their opinions, attitudes, and information regarding a company's products and services through various ways, such as by sharing their positive or negative opinions via product review websites (e.g., *epinions.com*), e-commerce sites (e.g., *amazon.com*), online social networking websites (e.g., *facebook.com*), and online customer networks (e.g., *scn.sap.com*). In addition, never before has the structure of social relations been so transparent and observable as today, thus, opening up the opportunity to measure social influence more precisely than ever before (Xu et al. 2008).

Moreover, multiple studies have found that social influence transmitted through (e)WoM, as in online customer networks, not only impacts customers' views, attitudes, and beliefs but also impacts customers' purchase decisions (Adjei et al. 2010; Amblee and Bui 2011; Hennig-Thurau and Walsh 2003; Scholz et al. 2013; Wang and Chang 2013). Adjei et al. (2010), for instance, demonstrated that online customer networks have a positive impact on customers' purchase intentions, wherein higher sales are generated from customers who frequently engage in conversations with other customers. On the one hand, these studies uncover social influence's significant monetary power through its impact on customers' purchase decisions. On the other hand, they uncover the importance for companies to measure and account for customers' social influence contribution in online customer networks.

The Imperative to Distinguish between Positive and Negative Social Influence

Previous research has shown that social influence impacts customers' decision making processes and buying behavior and is therefore of significant importance for companies (Adjei et al. 2010; Amblee and Bui 2011; Hennig-Thurau and Walsh 2003; Scholz et al. 2013; Wang and Chang 2013). However, due to the diverging effect of positive and negative social influence on customers' purchasing decisions, it is paramount to further distinguish between customers exerting positive and those exerting negative social influence when accounting for customers' social influence in online customer networks.

Not surprisingly, in regard to the effect of positive social influence, Clemons et al. (2006) showed that strongly positive ratings of customers positively affect product sales. Similar results have been found by Chang and Chin (2010) and their investigation of customers' buying process in respect to the purchase of notebook computers. In contrast, even more so has previous research shown that the diffusion of negative opinions about a brand can substantially harm a company's sales and profit (e.g., Romani et al. 2012). Consistent with these findings, research by Hartman et al. (2013) indicates that negative-only reviews pose strongly negative influence on customers' purchase intentions. Further, a study by Anderson (1998) observed that dissatisfied customers generate significantly more negative WoM as compared to positive WoM expressed by satisfied customers. Hence, negative WoM is often cited as having stronger influential effects on other customers than positive WoM (Goldenberg et al. 2007; Ma et al. 2008; Nitzan and Libai 2011). Besides this tendency of people to write more about what they do not like as opposed to what they like, research has also suggested that customers assign more weight to negative pieces of information as compared to positive pieces of information, referred to as negativity effect (e.g., Hennig-Thurau and Walsh 2003; Park and Lee 2009; Skowronski and Carlston 1987). Therefore, Ballantine and Au Yeung (2015), investigating three types of message valence, i.e. positive, ambiguous/mixed, and negative messages, also found that negative messages have a disproportionally larger impact on customers' brand attitude and purchase intention than positive or ambiguous/mixed messages. In particular, studies supporting the negativity effect tend to reason that negative pieces of information are simply perceived as more attention grabbing and receive greater scrutiny in the opinion forming process (Homer and Yoon 1992). Thus, it is of utter importance for companies to distinguish between positive and negative social influence when accounting for customers' social influence in online customer networks (Ballantine and Au Yeung 2015; Floh et al. 2013; Hennig-Thurau and Walsh 2003; Lee et al. 2008; Park and Lee 2009; Senecal and Nantel 2004). As a consequence, the diffusion of positive and negative social influence in an online customer network has the potential to make or break the long-term success story of a company. While customers exerting negative social influence pose a threat to the company's revenue, customers exerting positive social influence and those withstanding negative social influence of other customers in the online customer network have the power to increase the company's business success. Accordingly, in order to take advantage of the positive influential power of customers and avert the negative downside, the identification of a customer's contribution to the online customer network in terms of positive and negative social influence exerted on other customers appears vital. Companies who fail to make the distinction between positive and negative social influence, misconceive customers' value contribution in terms of their social influence on others in a network of customers, ultimately inheriting the potential to break the brand's success story. Hence, these companies will remain unable to mitigate the effect of negative social influence on the company's performance metrics and will likewise remain unable to fully take advantage of customers' positive social influence. The simple example with three customers (*A*, *B*, and *C*) in Figures 1 and 2 may serve as an illustration.

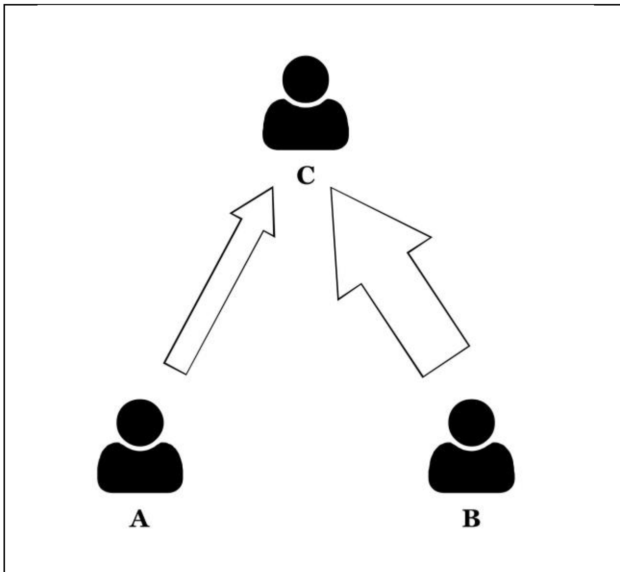

Figure 1. Sample online customer network with direction and strength of social influence

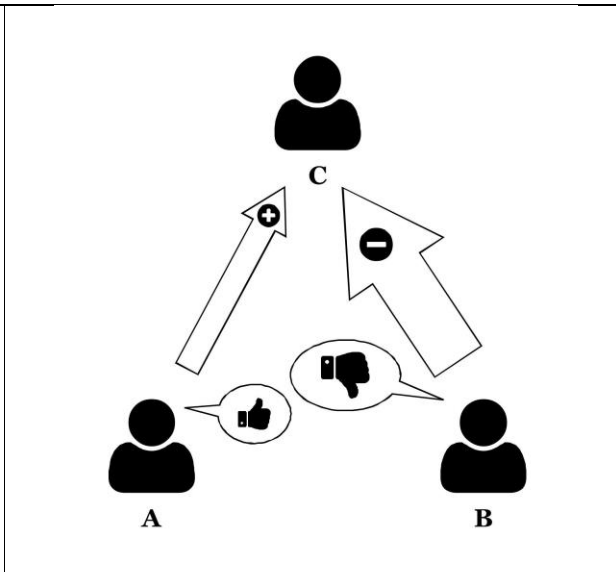

Figure 2. Sample online customer network distinguishing additionally between positive and negative social influence

In both illustrations, the arrows indicate direction and strength of social influence exerted among customers. Figure 1 depicts the scenario without and Figure 2 with considering the diverging effect of positive and negative social influence on customers' purchasing decisions. In Figure 1, no information about the polarity of the social influence is considered. If there is no distinction between positive and negative social influence, customer *B* would be recognized as the most important customer due to his/her strong social influence on the purchase decisions of customer *C*. In contrast, customer *A* would be regarded as less important due to his/her seemingly lower social influence on customer *C*. As long as customer *A* and *B* both positively influence customer *C*, this ranking of the importance and value contribution of the influence on customer *C*'s purchase decisions would be correct. However, when taking into account the polarity of customers' social influence, it becomes apparent that customer *B* has a strong negative influence on customer *C*'s purchase decisions (cf. Figure 2). Customer *A* in contrast, although with less strength, positively influences customer *C*. Thence, with distinguishing between positive and negative social influence, customer *A* is now regarded as more valuable compared to customer *B*. This simple example underlines that it is of utter importance to distinguish between positive and negative social influence when quantifying a customer's social influence in an online customer network in order to prevent misconception, i.e. under- and overestimation.

Accounting for Positive and Negative Social Influence

Several studies exist that elaborated on accounting for social influence in online customer networks. However, these approaches predominantly focus on accounting for positive social influence and do not consider the diverging effect of positive and negative influence on customers' purchasing decisions. As a consequence, research is scarce regarding approaches that specifically focus on the impact on the value contribution due to customer's positive and negative social influence on other customers. The subsequent sections will provide an overview of respective approaches that account for positive social influence and those that also consider negative influence in online customer networks.

Approaches Accounting for Positive Social Influence

A number of terms have been used to describe the value contribution of a customer's positive social influence in online customer networks: These include *referral value* (Kumar et al. 2006, 2010b), *social value* (Libai et al. 2013) for the value generated via incentivized referral programs, the *indirect social effect* in accounting for the value of a lost customer (Hogan et al. 2003), *WoM value* (Wangenheim and Bayón 2007), and *influence value* (Ho et al. 2012). Many of these studies based their accounting for positive social influence on influence arising from extrinsically motivated WoM through incentivized referral programs. Hence, with their attempt to account for social influence induced in form of referrals, denoted as *customer referral value* (CRV), Kumar et al. (2007), for instance, proposed an approach to compute how much of a customer's monetary value stems from the customer's social influence transmitted via incentivized referrals. Thereby, the authors distinguish between two types of referrals: Type-one referrals by newly acquired customers due to a referral made by an existing customer and type-two referrals by newly acquired customers whose acquisition is not attributable to another customer's referral. Consequently, the CRV is calculated for each customer as the sum of the present value of the customer's type-one referrals and the present value of the customer's type-two referrals. While Libai et al. (2013) also accounted for social influence generated from incentivized eWoM, they rather focused on assessing the *social value* of the seeding group as a whole, hence the group of customers that has been chosen to be exposed to the incentivized referral program, instead of each customer's individual contribution. Hence, the computation of the *social value* is based on the use of agent-based models comparing the customer equity created by the group of incentivized customers with the customer equity created by the same group of customers in absence of the referral program. In contrast to the CRV by Kumar et al. (2007), they not only consider the effects of WoM on the acquisition of new customers but also the effects of WoM on existing customers' purchase behavior within the boundaries of the customer network.

Further studies extended accounting for positive social influence based on referrals by considering social influence arising not only from incentivized, extrinsically motivated, but also from non-incentivized, intrinsically motivated positive WoM (Däs et al. 2017; Klier et al. 2014; Kumar et al. 2010a; Kumar et al. 2013; Wangenheim and Bayón 2007). In comparison to previous models of positive social influence, Däs et al. (2017) presented a novel approach that includes the effects of direct as well as indirect social influence in online customer networks. The approach reallocates values according to customers' social influence through WoM messages diffused in online customer networks and thereby acknowledges that customers might also "owe" parts of their value contribution to other customers' influential power.

Approaches Accounting for Negative Social Influence

In research only few models account for negative social influence, such as negative WoM (Goldenberg et al. 2007; Kumar et al. 2010a; Kumar et al. 2013; Ma et al. 2008). As one of the first, Ma et al. (2008) proposed an information diffusion model on the individual's level to account for negative social influence among individuals. The authors described the process of people influencing each other similar to the physical heat diffusion phenomenon. Early adopters of a product start the diffusion process of positive or negative information within an online social network. With advancing time, the "heat", thus product information, is diffused to the entire network. Hence, a customer's social influence ("heat") is computed as the product of the initial heat at a particular node (hence customer) and a so called diffusion kernel (Ma et al. 2008). Thereby, the initial heat of a customer or node at a particular time represents the heat the customer receives from others minus the heat diffused by this customer to other customers within the network (Ma et al. 2008). Negative influence is specifically accounted for by assigning a negative value to the aforementioned initial heat of a customer, if the customer spreads negative influence. However, the authors remain vague in regard to the identification of negative influence. They basically assume that a customer spreads negative influence, if the customer is not in favor of the respective product.

In contrast, with the *customer influence effect* (CIE) and the *customer influencer value* (CIV), Kumar et al. (2010a; 2013) presented approaches to account for negative social influence exerted through non-incentivized, intrinsically motivated, thus "naturally appearing" WoM. In addition, similar to Libai et al. (2013), both the *customer influencer value* (CIV) and the *customer influence effect* (CIE) measure social influence in regard to the acquisition of new customers as well as the purchase behavior of existing customers within the boundaries of the online customer network (Kumar et al. 2010a; Kumar et al. 2013). Thereby, Kumar et al. (2013) specifically considered negative social influence by extending Hubbell's (1965) measure of influence which „*departs from the classical sociometric tradition by permitting links to have fractional and/or negative strength*" (Hubbell 1965). The strength of the negative social influence is assessed by the number of messages a customer posts in the network. Although focusing primarily on positive social influence in their approach for customer valuation, Däs et al. (2017) mention the importance of not realized value contribution due to negative social influence among customers. In a brief extension of their model, the authors sketch a possible way how to analogously account for direct as well as indirect negative social influence (Däs et al. 2017).

Research Gap and Contribution to Theory and Practice

As of today, most of the existing literature on the effects of social influence focuses on the diffusion of WoM but does neither concentrate on the quantification of social influence on an individual customer level nor distinguish between positive and negative social influence. Previous research on customers' social influence in online customer networks focuses predominantly on positive social influence (e.g., Ho et al. 2012; Hogan et al. 2003; Wangenheim and Bayón 2007), thereby ignoring the diverging effect of positive and negative social influence on other customers' purchase decisions. However, disregarding the destructive power of negative social influence for example leads to substantially overestimating the value contribution of customers who talk unfavorable about the company's brand or products, thus influencing other customers negatively. Although the destructive effect of negative social influence is widely known, research regarding the accounting for negative social influence in online customer networks is still insufficient (e.g., Kumar et al. 2013; Ma et al. 2008; Moldovan and Goldenberg 2004). In addition, the majority of existing research focused mainly on social influence through the diffusion of WoM, for example in form of incentivized seeding campaigns and considered only extrinsically motivated WoM (Kumar et al. 2007; Libai et al. 2013). Only few studies explicitly concentrated on WoM spread naturally by customers themselves without specific incentive (e.g., Klier et al. 2014; Kumar et al. 2010a; Kumar et al. 2013). Furthermore, existing approaches mostly lack the consideration of direct and indirect effects of social influence and base the actual assessment of negative social influence mainly on basic assumptions such as the assumption that customers favoring a product automatically exert positive social influence contrary to customers not in favor of a product automatically exert negative social influence (e.g., Hogan et al. 2004; Ma et al. 2008; Oestreicher-Singer et al. 2013). Partial aspects of negative social influence are regarded by Kumar et al. (2013), where the CIE provides a measure for social influence as in the ability of a user to spread positive and negative WoM, while the CIV links customers' social influence to their actual revenue based on purchases. Däs et al. (2017) provide a first sketch how to consider negative social influence for customer valuation. However, none of these approaches provides a detailed integrated approach for the calculation of customers' individual value contribution in an online customer network by accounting for direct and indirect positive and negative social influence induced between customers naturally, without incentivized referral programs.

Against this background, the aim of our research as well as its contribution to existing literature is to develop an approach to account for customers' positive and negative social influence returning each customer's "true" integrated value contribution in the context of an online customer network. Thereof, the contribution of our research to theory is threefold: First, we propose a novel integrated approach to account for both positive and negative social influence in online customer networks. Second, our proposed approach considers direct as well as indirect effects of customers' social influence among customers in online customer networks. Third, our approach avoids double counting by reallocating value contributions between customers. Consequently, our approach does not change the overall sum of value contributions within the online customer network. As a result, the proposed approach allows for an individual calculation of each customer's integrated value contribution within an online customer network. Our approach therefore equips practitioners with the knowledge to make the destructive power of negative social influence and the enriching power of positive social influence on customers' purchase decision processes more feasible. This knowledge can be the basis for a more effective segmentation and targeting of customers.

Novel Approach to Account for Customers' Social Influence in Online Customer Networks

Modelling Customers' Positive Social Influence

For our approach, we consider a firm-sponsored online customer network with customers as members who purchase the company's products and services as well as interact with each other. Positive social influence can thereby be exerted intentionally, for example through direct communication in form of a personal message, or unintentionally, for example through imitation of observed behaviors (Blazevic et al. 2013). Intentionally exerted positive WoM, for example in form of a personal message between two customers within an online customer network, is thereby seen as the most influential factor regarding customers' purchase decisions (Brown and Reingen 1987; Sweeney et al. 2014). In contrast, a random, not specifically product-related verbal conversation between two customers can for example induce unintentionally positive social influence. However, unintentionally social influence is regarded as not as strong as intentionally social influence (Blazevic et al. 2013).

When accounting for customers' positive social influence it is essential to determine the strength of social influence as best as possible. Strength of social influence is thereby defined as the frequency and depth of customers' interaction (Marsden and Campbell 1984) and depends, among others, on the form of social influence (e.g., WoM, private conversation, etc.) , the stability of the connection (e.g., close friend or loose contact), and the intended goals of sender and receiver (e.g., obvious advertising or honest product recommendation) (Blazevic et al. 2013). Strength of social influence is determined based on the social interactions within an online customer network, for example in form of the number of messages a customer i is sending to another customer j (Cheung and Lee 2010; Kane et al. 2014). Both customer i and customer j are members of the online customer network whereupon customer j is among all customers positively influenced by customer i ($positively\ influenced(i)$). Thereby, the stability of connection and intended goals of sender and receiver can vary and therefore influence the strength of influence. For our approach, we define the positive strength of direct social influence customer i is exerting on customer j as $s_{positive}^{i \to j}$. Since it is possible that not only customer i but many other customers exert positive social influence on customer j ($positive\ influence(j)$), the relative strength for each customer i is determined by means of $\frac{s_{positive}^{i \to j}}{\sum_{k \in positive\ influence(j)} s_{positive}^{k \to j}}$, where $\sum_{k \in positive\ influence(j)} s_{positive}^{k \to j}$ represents the sum of all positive social influence exerted on customer j.

Prior research emphasized that not all but rather a share of a customer's individual value contribution is based on the positive social influence induced by another customer on him/her (e.g., Kane et al. 2014). This is due to the fact that an individual customer is probably never completely influenced in his/her purchase decision by other persons but he/she rather includes several aspects in a specific purchase decision of which one can be for example the positive social influence in form of a private message received from another customer (Adjei et al. 2010). In general, the amount of the share depends on the form of social influence. For example, direct WoM has more influence on customers' purchase decisions in contrary to an anonymous consumer feedback on a review site (e.g., Meuter et al. 2013). Based on these considerations, we introduce the parameter α to be able to account for a corresponding share of customer *i*'s value contribution vc_i tracing back to the positive social influence induced by other customers in the online customer network (Däs et al. 2017). The optimal choice of α depends on how much of a customer's value contribution should be attributed to the influencing customers, i.e. $\alpha = 0$ would imply that no value contribution is induced by positive social influence; α close to 1 implies that the value contribution is strongly based on positive social influence induced by other customers. Depending on the specific online customer network and the availability of reliable and comprehensive data on individual customer level, α can be defined either customer specific, customer segment specific or for all customers the same (average).

The potential effect of positive social influence on the receiver is manifold. On the one hand, a customer is positively influenced in regard to his/her purchase decisions resulting in higher sales. On the other hand, the influenced customer is the basis for inducing even more positive social influence on other customers, for example as a result of the positive experience when buying a product after being influenced by another customer. The respective influential customer is therefore not only responsible for the value contribution of the customer directly influenced by him/her but also positively influences the purchase decisions of the customers connected to him/her indirectly through other customers (Algesheimer and von Wangenheim 2006; Goldenberg et al. 2009; Klier et al. 2014). However, the social influence a customer induces on another customer's purchase decision is stronger when a direct connection between these two customers exists (Blazevic et al. 2013; Kane et al. 2014). Therefore, social influence induced only indirectly does not have the same effect on the influenced customer compared to direct social influence. Indirect social influence can for example appear in form of a third customer passing on the recommendation of the originally influencing customer. The diminishing effect is thereby stronger, the more customers are between the original influencing and the influenced customer. This so-called "*ripple effect*" (Hogan et al. 2004) has to be considered when accounting for the indirect social influence of customers in an online customer network (Däs et al. 2017; Klier et al. 2014). We account for indirect social influence by including a share of the value contribution of the influenced customer *j* in our calculation of the positive influence of customer *i* in form of $vc_j^{positive\ influence}$. Based on the parameter α, parts of the value contribution of customer *j* are attributed to the influencing customer *i* in order to account for his/her positive social influence on customer *j* and therefore in turn for the possible positive social influence induced by customer *j* on other customers.

In order to account for positive social influence, a certain part of the value contribution of the influenced customer *j* is attributable to the influencing customer *i*. In contrast, customer *i* not only induces positive social influence but is at the same time positively influenced in his/her purchase decisions by other customers. Therefore, customer *i* loses a share of his/her value contribution to these customers. The value contribution of a customer depends on the amount of his/her positive social influence on other customers, both direct and indirect, as well as on the degree to which he/she is influenced by other customers. Therefore, we define the value contribution $vc_i^{positive\ influence}$ for customer *i* due to his/her positive influence on other customers in an online customer network as follows:

$$vc_i^{positive\ influence} = \sum_{j \epsilon positively\ influenced(i)} \frac{s_{positive}^{i \to j}}{\sum_{k \in positive\ influence(j)} s_{positive}^{k \to j}} \left(\alpha \cdot vc_j + \alpha \cdot vc_j^{positive\ influence}\right), \quad (1)$$

where	$positively\ influenced(i)$	is the set of customers directly positively influenced by customer i,
	$s_{positive}^{i \to j} \in \Re$	the strength of direct positive social influence exerted by customer *i* on customer *j*,
	$positive\ influence(j)$	the set of customers exerting direct positive social influence on customer *j*,
	$\alpha \in [0,\ 1[$	the share of value contribution tracing back to positive social influence within the online customer network,
	$vc_j \in \Re$	the value contribution generated individually by customer *j*, and
	$vc_j^{positive\ influence} \in \Re$	the value contribution due to direct and indirect positive social influence exerted by customer *j*.

Accordingly, the value contribution $vc_i^{positively\ influenced}$ of customer i tracing back to positive social influence of other customers on customer i within the online customer network is defined as follows:

$$vc_i^{positively\ influenced} = \sum_{j \epsilon positive\ influence(i)} \frac{s_{positive}^{j \to i}}{\sum_{k \epsilon positive\ influence(i)} s_{positive}^{k \to i}} (\alpha \cdot vc_i + \alpha \cdot vc_i^{positive\ influence}), \qquad (2)$$

where $positive\ influence(i)$ is the set of customers inducing direct positive social influence on customer i,

$s_{positive}^{j \to i} \in \Re$ the strength of direct positive social influence exerted by customer j on customer i,

$positive\ influence(i)$ the set of customers exerting direct positive social influence on customer i,

$\alpha \in [0,\ 1[$ the share of value contribution tracing back to positive social influence within the online customer network,

$vc_i \in \Re$ the value contribution generated individually by customer i, and

$vc_i^{positive\ influence} \in \Re$ the value contribution due to direct and indirect positive social influence exerted by customer i.

Summed up, by regarding positive social influence when calculating customers' value contribution, companies are able to account not only for the individual value contribution generated by the customer itself but also for the value contribution due to direct and indirect positive social influence induced between customers in the online customer network. Following our approach, customers who induce positive social influence on other customers will be regarded as more valuable for the company in contrast to customers being positively influenced by other customers in their purchase decisions.

Modelling Customers' Negative Social Influence

In order to account for a customer's "true" integrated value contribution including both positive as well as negative direct and indirect social influence, it is of major importance to consider the effect of negative social influence (Anderson 1998; Goldenberg et al. 2007; Ma et al. 2008; Nejad et al. 2014; Romani et al. 2012). Both in research and practice, there is a consistent opinion that negative social influence induced by one customer towards another results in loss of business, hence a not realized potential value contribution (Arndt 1967; Däs et al. 2017; Kumar et al. 2010a; Weinberg and Berger 2011). Thereby, it is assumed that a value contribution, referred to as *lost value contribution* (lvc), would have been made by the negatively influenced customer in the absence of negative social influence. In some cases, negative social influence induced by one customer on another can thereby in some way outplay a former actual positive opinion regarding a specific product. One of the most important influencing factors for a purchase decision is the social context, hence the opinion of other customers. This is seen as the result of evolution since following the behavior of others was recognized already by early humans as the best way to achieve the desired goals (e.g., Reis et al. 2000). Therefore, customers influencing others in a negative way are responsible for the corresponding loss of value contribution. In the same way as for positive social influence, this direct negative social influence on customers' purchase decisions can be observed beyond the first degree of separation and thus indirectly influences – however with a diminishing effect – other customers negatively within the online customer network (Hogan et al. 2004).

For our approach, we account for the strength of negative social influence customer i is inducing on customer j, defined as $s_{negative}^{i \to j}$, by observing the frequency and depth of customers' interaction. Customer j is thereby part of the overall set of customers ($negatively\ influenced(i)$) being directly negatively influenced by customer i. Accordingly, the relative strength of negative social influence is calculated by distributing the share of negative social influence induced by customer i on customer j according to the sum of the total negative social influence induced on customer j by all customers ($negative\ influence(j)$) in form of $\frac{s_{negative}^{i \to j}}{\sum_{k \epsilon negative\ influence(j)} s_{negative}^{k \to j}}$.

The negative social influence induced by customer i on customer j leads to a lost value contribution not realized by customer j. Similar to the case of positive social influence, the parameter β accounts for the corresponding share of the lost value contribution tracing back to indirect negative social influence in the online customer network. We define the parameters α and β separately to take into account the fact that negative social influence is regarded to have a stronger negative impact on customers' purchase decisions than positive social influence has a positive impact (Edwards and Edwards 2013; Homer and Yoon 1992). According to our approach, the individual value contribution of customer i has to be reduced by the amount of the corresponding lost value contribution $lvc_i^{negative\ influence}$. In contrast, customer i's individual value contribution has to be increased by the amount of potential value contribution not realized due to being negatively influenced by other customers in the network $lvc_i^{negatively\ influenced}$. We define the lost value contribution $lvc_i^{negative\ influence}$ not realized due to negative social influence induced by customer i as follows:

$$lvc_i^{negative\ influence} = \sum_{j\epsilon negatively\ influenced(i)} \frac{s_{negative}^{i\rightarrow j}}{\sum_{k\epsilon negative\ influence(j)} s_{negative}^{k\rightarrow j}} (lvc_j + \beta \cdot lvc_j^{negative\ influence}), \quad (3)$$

where	$negatively\ influenced(i)$	is the set of customers directly negatively influenced by customer i,
	$s_{negative}^{i\rightarrow j} \in \Re$	the strength of direct negative social influence exerted by customer i on customer j,
	$negative\ influence(j)$	the set of customers exerting direct negative social influence on customer j,
	$\beta \in [0,\ 1[$	the share of lost value contribution tracing back to indirect negative social influence within the online customer network,
	$lvc_j \in \Re$	the lost value contribution of customer j due to negative social influence of other customers in the network, and
	$lvc_j^{negative\ influence} \in \Re$	the lost value contribution due to direct and indirect negative social influence exerted by customer j.

Accordingly, we define the lost value contribution $lvc_i^{negatively\ influenced}$ not realized due to customer i being negatively influenced by other customers as follows:

$$lvc_i^{negatively\ influenced} = \sum_{j\epsilon negative\ influence(i)} \frac{s_{negative}^{j\rightarrow i}}{\sum_{k\epsilon negative\ influence(i)} s_{negative}^{k\rightarrow i}} (lvc_i + \beta \cdot lvc_i^{negative\ influence}), \quad (4)$$

where	$negative\ influence(i)$	is the set of customers inducing direct negative social influence on customer i,
	$s_{negative}^{j\rightarrow i} \in \Re$	the strength of direct negative social influence exerted by customer j on customer i,
	$negative\ influence(i)$	the set of customers exerting direct negative influence on customer i,
	$\beta \in [0,\ 1[$	the share of lost value contribution tracing back to indirect negative social influence within the online customer network,
	$lvc_i \in \Re$	the lost value contribution of customer j due to negative social influence of other customers in the network, and
	$lvc_i^{negative\ influence} \in \Re$	the lost value contribution due to direct and indirect negative social influence exerted by customer i.

Summed up, direct as well as indirect negative social influence induced between customers of an online customer network has impact on their individual value contribution. As a consequence, we attribute on the one hand a lost value contribution to customers who are negatively influenced in their purchase decisions in order to account for their not realized potential purchases. On the other hand, the not realized lost value contribution is subtracted from the negatively influencing customers in order to reveal each customer's true value in regard to their negative social influence on other customers' purchase decisions.

Integrated Approach to Account for Customers' Positive and Negative Social Influence in Online Customer Networks

We propose an integrated approach that accounts for both customers' positive as well as negative social influence in online customer networks. Besides a customer's individual value contribution, the approach also encompassed the value contribution due to direct and indirect positive and negative social influence induced between customers (cf. Equations 1-4). Thus, the respective integrated value contribution can either increase or decrease compared to the original individual value contribution neglecting direct and indirect as well as positive and negative social influence between customers. A customer's integrated value contribution increases when he/she positively influences other customers' purchase decisions (cf. Equation 1). We additionally propose the increase of customers' integrated value contribution by the amount of the lost value contribution they would achieve without being negatively influenced by other customers in their own purchase decision (cf. Equation 4). In contrast, the customers' integrated value contribution decreases by the amount of value contribution attributed to the positive social influence induced by other customers (cf. Equation 2) and the amount of lost value contribution not realized due to the customers' negative social influence induced on other customers (cf. Equation 3). Therefore, we present the approach to calculate the integrated value contribution of customer i ivc_i as follows:

$$ivc_i = vc_i + \left(vc_i^{positive\ influence} - vc_i^{positively\ influenced}\right) + \left(lvc_i^{negatively\ influenced} - lvc_i^{negative\ influence}\right), \quad (5)$$

where	$vc_i \in \Re$	is the value contribution generated individually by customer i,
	$vc_i^{positive\ influence}$	the value contribution due to positive social influence of customer i induced on other customers,
	$vc_i^{positively\ influenced}$	the value contribution due to positive social influence induced on customer i by other customers,
	$lvc_i^{negatively\ influenced}$	the lost value contribution due to negative social influence induced on customer i by other customers, and
	$lvc_i^{negative\ influence}$	the lost value contribution due to negative social influence of customer i induced on other customers.

Our approach expands existing research by accounting for direct and indirect as well as positive and negative social influence induced between customers in online customer networks. The approach thereby avoids double counting of customers' value contributions and does not change the overall sum of all value contributions within an online customer network since customers' original value contributions are distributed based on direct and indirect positive and negative social influence rather than counted twice, once for the influenced customer and once for the influencing customer. Companies are therefore able to calculate the "true" integrated value contribution of their customers participating in the company's online customer network. Our proposed approach expands existing literature by providing an integrated approach and overcomes at the same time shortcomings of existing models like the mere focus on positive social influence, the consideration of only direct social influence, and double counting of reallocated value contributions (Berger and Nasr 1998; Däs et al. 2017; Kumar et al. 2010a; Oestreicher-Singer et al. 2013; Weinberg and Berger 2011).

Approaches for the Operationalization of Social Influence

In order to apply our approach in practice, Social Media Analytics (SMA) can be used to detect, analyze, and determine the polarity, frequency, and depth of social influence between customers in an online customer network (Stieglitz et al. 2014). SMA comprises methods which are described as „*informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data*" (Zeng et al. 2010). Especially content and sentiment analysis techniques are important to analyze vast amounts of online customer network data (Krippendorff 2013; Stieglitz et al. 2014; Vinodhini and Chandrasekaran

2012). Thereby, SMA techniques like sentiment analysis enable the assessment not only of the polarity of social influence but also the strength of the positive and negative social influence (Kim et al. 2016).

In a first step, to determine the polarity of customers' social influence on each other, the content of the customer interaction, which is for example the content of a personal message sent from one customer to another, is analyzed with the help of sentiment analysis techniques (e.g., Pang and Lee 2008). Based on these results, in a second step the specific strength of the detected positive social influence $s_{positive}^{i \to j}$ or negative social influence $s_{negative}^{i \to j}$ is determined in detail. The strength depends in general on whether the content of a message is at all relevant for positively or negatively influencing a customer's purchase decision, and if so, how often and how strong this influence is exerted (e.g., Blazevic et al. 2013). To determine the strength of social influence, the message is analyzed based on unsupervised and supervised sentiment classification techniques on document or word level (Liu 2012; Stieglitz et al. 2014). For example, by applying these advanced sentiment analysis techniques, negative social influence induced by customer i on customer j in form of a personal message can be attributed to a particular strength of social influence (e.g., $s_{negative}^{i \to j} = 5$). The results of the sentiment analysis of all customer interactions allows finally for the determination of the parameters for all customers k inducing positive social influence on customer i, defined as $positive\ influence(i)$, and accordingly the parameters for all customer k inducing negative social influence on customer i, defined as $negative\ influence(i)$. Summing up, SMA techniques like sentiment analysis are suitable to support companies in the application of our approach to account for customers' positive and negative social influence in their online customer network.

Illustrative Example

As part of the Design Science research process (e.g., Hevner et al. 2004), we demonstrate for an exemplary online customer network, as illustrated in Figure 3, the applicability of our proposed approach to account for customers' social influence. All members of the online customer network are customers of the company and can purchase its products online via an online shop attached to the online customer network. Within the online customer network, customers can interact with each other in form of sending private messages. Thereby, customers are directly and indirectly as well as positively and negatively influencing the purchase decisions of other customers. The amount of customers' value contribution (vc_i) for the products purchased in the company's online shop in the period of observation as well as the amount of customers' lost value contribution lvc_i for not realized purchases due to being negatively influenced by at least one other customer are specified in Figure 3. Further, the direction and strength of social influence induced through direct messages is displayed as well as whether this influence is positive ($s_{positive}^{i \to j}$) or negative ($s_{negative}^{i \to j}$).

The three customers *Aron*, *Bob*, and *Claudia* participating in the online customer network exchange private messages and thereby induce positive and/or negative social influence on each other's purchase decisions regarding the products of the company. As displayed in Figure 3, *Claudia* sends private messages to both *Aron* and *Bob* advising against buying a certain product while *Bob* in turn recommends in another message a specific product to *Aron*. Additionally, via *Aron*, *Claudia* also induces indirect negative social influence on *Bob*. In our example, we assume that the share of value contributions tracing back to the positive social influence is 50% ($\alpha = 0.50$) and the share of lost value contribution tracing back to negative social influence is 70% ($\beta = 0.70$). Using the illustrative example, we calculate the integrated value contribution ivc_i for *Aron*, *Bob*, and *Claudia*.

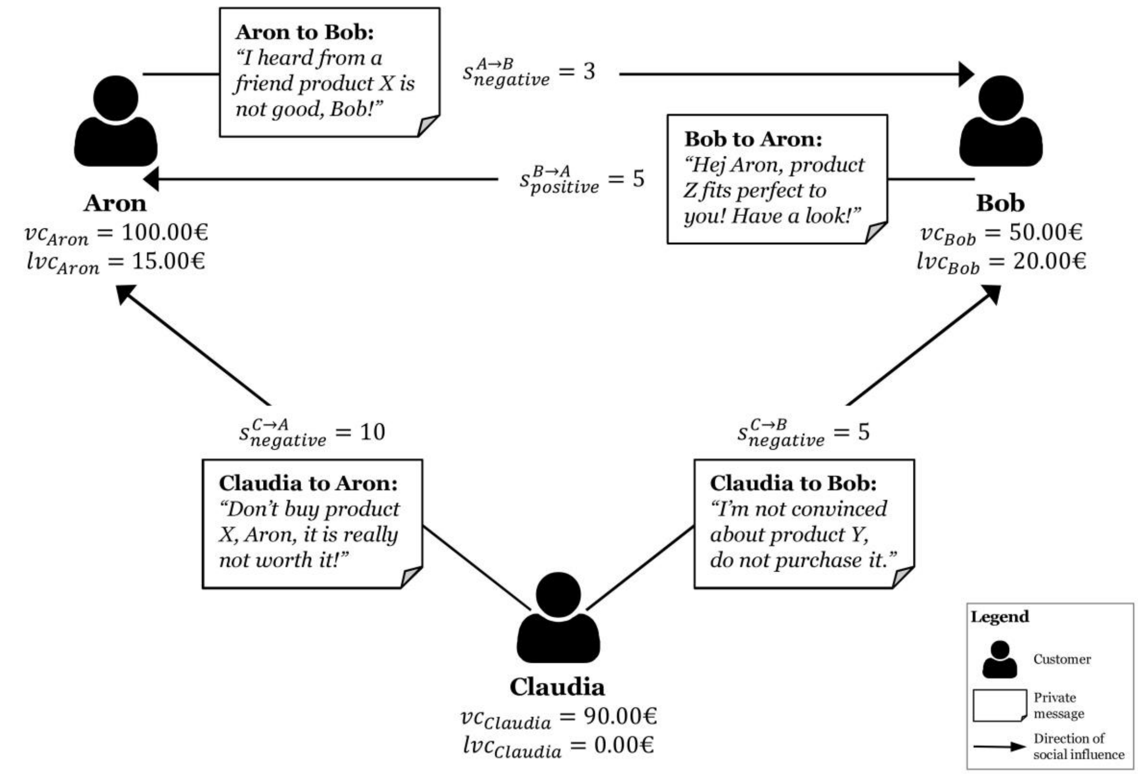

Figure 3. Exemplary Online Customer Network

As displayed in Figure 3, *Aron* is on the one hand influenced by *Bob* who is recommending the company's product *Z* to *Aron* ("*Hej Aron, product Z fits perfect to you! Have a look!*"). The content of the message and subsequently the social influence induced by *Bob* on *Aron* is positive ($s_{positive}^{B \to A} = 5$). On the other hand, *Aron* received a message from *Claudia* with the content "*Don't buy product X, Aron, it is really not worth it!*". The analysis of the content of the sent message reveals a clearly negative social influence on *Aron's* purchase decision ($s_{negative}^{C \to A} = 10$) since *Claudia* advises *Aron* against the purchase of product *X*. This brings *Aron* to forward *Claudia*'s negative criticism of product *X* to *Bob* ("*I heard from a friend product X is not good, Bob!*"). Bob is therefore indirectly negatively influenced by *Claudia* via *Aron*. Furthermore, *Claudia* also induces direct negative influence on *Bob* ($s_{negative}^{C \to B} = 5$) regarding another of the company's products ("*I'm not convinced about product Y, do not purchase it*"). In combination with the given individual value contributions vc_i and the lost value contributions lvc_i, we calculate the integrated value contribution ivc_i for each of the three customers as follows:

First, we calculate *Bob*'s value contribution due to his positive social influence on *Aron*: $vc_{Bob}^{positive\ influence} = \frac{5}{5} * (0.5 * 100.00€ + 0.5 * 0.00€) = 50.00€$ (cf. Equation 1). Second, we calculate the value contribution of *Aron* attributed to *Bob*'s positive social influence: $vc_{Aron}^{positively\ influenced} = \frac{5}{5} * (0.5 * 100.00€ + 0.5 * 0.00€) = 50.00€$ (cf. Equation 2). Third, we calculate the lost value contribution due to inducing direct and indirect negative social influence on other customers. On the one hand, the lost value contribution not realized due to *Aron*'s negative social influence on *Bob*'s purchase decision is calculated: $lvc_{Aron}^{negative\ influence} = \frac{3}{8} *$

$(20.00€ + 0.7 * 0.00€) = 7.50€$ (cf. Equation 3). On the other hand, the lost value contribution due to *Claudia*'s negative social influence on *Aron* and *Bob* is calculated: $lvc_{Claudia}^{negative\ influence} = \frac{10}{10} * (15.00€ + 0.7 * 7.50€) + \frac{5}{8} * (20.00€ + 0.7 * 0.00€) = 32.75€$ (cf. Equation 3), considering thereby also her indirect negative influence on *Bob* via *Aron*. Fourth, we calculate the lost value contribution of *Aron* and *Bob* not realized due to being negatively influenced by other customers: $lvc_{Aron}^{negatively\ influenced} = \frac{10}{10} * (15.00€ + 0.7 * 7.50€) = 20.25€$ and $lvc_{Bob}^{negatively\ influenced} = \frac{3}{8} * (20.00€ + 0.7 * 0.00€) + \frac{5}{8} * (20.00€ + 0.7 * 0.00€) = 20.00€$ (cf. Equation 4).

Finally, the integrated value contribution ivc_i for each customer is calculated. *Aron*'s integrated value contribution is therefore calculated as $ivc_{Aron} = 100.00€ + (0.00€ - 50.00€) + (20.25€ - 7.50€) = 62.75€$ (cf. Equation 5). Accordingly, the integrated value contributions for *Bob* ($ivc_{Bob} = 50.00€ + (50.00€ - 0.00€) + (20.00€ - 0.00€) = 120.00€$) and *Claudia* ($ivc_{Claudia} = 90.00€ + (0.00€ - 0.00€) + (0.00€ - 32.75€) = 57.25€$) are calculated. The results of the illustrative example based on the proposed Equations (1-5) are summarized in Table 1.

Table 1. Example Calculation of the Integrated Value Contribution

	Aron	***Bob***	***Claudia***
vc_i	100.00	50.00	90.00
$vc_i^{positive\ influence}$ [€]	0.00	50.00	0.00
$vc_i^{positively\ influenced}$ [€]	50.00	0.00	0.00
$lvc_i^{negative\ influence}$ [€]	7.50	0.00	32.75
$lvc_i^{negatively\ influenced}$ [€]	20.25	20.00	0.00
ivc_i [€]	62.75	120.00	57.25

Following our approach, *Aron* loses parts of his original value contribution to *Bob*, on the one hand due to the positive social influence induced by *Bob* on him ($vc_{Aron}^{positively\ influenced} = 50.00€$) and on the other hand because *Aron* himself induces in turn negative social influence on *Bob* ($lvc_{Aron}^{negative\ influence} = 7.50€$). However, *Aron* regains value because of the negative social influence induced by *Claudia* on him ($lvc_{Aron}^{negatively\ influenced} = 20.25€$). *Bob* receives value contribution based on the one hand on the positive social influence induced on *Aron* ($vc_{Bob}^{positive\ influence} = 50.00€$) and on the other hand he regains lost value contribution due to being negatively influenced by *Aron* and *Claudia* ($lvc_{Bob}^{negatively\ influenced} = 20.00€$). Finally, *Claudia* experiences a reduction of her individual value contribution due to the negative social influence she induces directly and indirectly on the other two customers *Aron* and *Bob* ($lvc_{Claudia}^{negative\ influence} = 32.75€$). Please note that the overall sum of value contribution with in total 240.00€ does not change within the online customer network. However, applying our proposed approach changes the distribution of value contribution among customers due to the consideration of network effects based on direct and indirect as well as positive and negative social influence between customers.

Compared to the original individual value contribution vc_i – hence without considering positive and negative direct and indirect social influence – the integrated value contribution ivc_i has changed: for *Aron* we observe a strong decrease for the integrated value contribution compared to the original value contribution (100.00€ → 62.75€). *Bob*, however, increases his integrated value contribution quite tremendously compared to his original value contribution (50.00€ → 120.00€). Finally, for *Claudia* we experience, in parallel to *Aron*, a sharp decline in the integrated value contribution compared to her original value contribution (90.00€ → 57.25€). By accounting for direct and indirect as well as positive and negative social influence in the calculation of the customers' integrated value contribution, we observe a striking change in a value contribution focused ranking. Both *Aron* and *Claudia* lose their ranks and are no longer regarded as the most valuable customers: *Aron* descends from the first position as the most valuable customer with a value contribution of 100.00€ to the second position with an integrated value contribution of merely 62.75€ and *Claudia* from the former second position with 90.00€ to the last position with an integrated value contribution of 57.25€. Furthermore, the key difference of our approached is displayed in the change of *Bob*'s ranking position. The former least valued customer regarding his individual value contribution is now considered as the most valuable customer due to the accounting for direct and indirect positive and negative social influence induced by him and the direct and indirect positive and negative social influence induced on him within the online customer network.

Discussion on Implications, Limitations, and Future Research

Implications for Theory and Practice

We proposed a novel approach to account for customers' direct and indirect positive as well as negative social influence in online customer networks. Our approach focuses thereby on the fact that there is a significant difference between customers who exert negative social influence and customers who exert positive social influence on other customers. The practical applicability of our approach was demonstrated using an illustrative example. The approach contributes to theory and practice in different ways.

First of all, our approach allows a well-founded valuation of a customer's integrated value contribution by considering positive as well as negative social influence between customers in a firm-sponsored online customer network. Thereby, we model the negative social influence as the lost value contribution not realized due to negative social influence induced between customers in an online customer network. Thus, in contrast to existing research like the *referral value* by Kumar et al. (2010b), the *social value* by Libai et al. (2013), or the *customer lifetime network value* by Däs et al. (2017), our approach expands existing research that focuses merely on positive social influence exerted between customers and neglects thereby the impact of negative social influence on customers' purchase decisions. Based on our novel approach, firms can better understand customers' social influence on each other's purchase behavior and are able to assess the "true" value contribution of their customers in the online customer network.

Second, we consider in our approach beside direct also indirect social influence between customers. Since in online customer networks customers are strongly connected to each other, positive as well as negative social influence spreads virally through the network (Hogan et al. 2004; Oestreicher-Singer et al. 2013). Existing studies often ignore social influence induced indirectly via other "intermediary" customers (e.g., Kumar et al. 2010a; Weinberg and Berger 2011). Based on the positive social influence induced by a customer, a share of the value contribution of the positively influenced customers is attributed to him/her. In contrast, a negatively influencing customer is accountable for the lost value contribution caused by his/her negative social influence on other customers' purchase decisions within the online customer network.

Third, while our approach reallocates the value contribution between customers based on the exertion of positive social influence and the lost value contribution based on negative social influence, the overall value contribution within the online customer network does not change. In contrast to existing research, we thereby avoid double counting of customers' value contribution, an often criticized limitation of customer valuation models (Klier et al. 2014; Kumar et al. 2010a; Weinberg and Berger 2011). In our approach, we do not double count customers' value contribution, once for the customer inducing positive or negative social influence and once for the influenced customer but in fact decrease or increase the individual value contribution based on the positive or negative social influence induced by a customer on other customers respectively induced by other customers on him/her. Our approach enables a suitable evaluation of a company's customer equity based on the customers' integrated value contributions. Therefore, companies will change their view on their customers dramatically since former under- as well as overestimated customers are now assigned with their "true" value. This allows practitioners a more accurate segmentation of their customer base, the targeted addressing of currently and potential valuable customers, and the optimization of the company's offerings.

Limitations and Future Research

Beside the highlighted research contribution presented in this paper, our approach is also subject to limitations which can serve as promising starting points for further research. First, beside a thorough theoretical foundation, we have derived our proposed approach to account for customers' social influence in detail and demonstrated the general applicability by means of an exemplary online customer network. As part of the Design Science research process (Gregor and Hevner 2013; Hevner et al. 2004; Peffers et al. 2007), we see the application of our approach with data from existing online customer networks as an important and desirable next step. Based on real-world data the practical applicability and impact of our approach on companies' customer valuation can be evaluated. Additionally, in the context of a real-world example, an in-depth analysis of single aspects of the approach can be conducted. Among the most interesting aspects for evaluation are, for example an in-depth empirical analysis of the parameters for the shares of (lost) value contribution tracing back to positive social influence (α) and indirect negative social influence (β): How much of a customer's value contribution is in fact induced or lost due to positive or negative social influence? Is the diminishing effect distinguishable between positive and negative social influence? Are the respective parameters similar for all customers or is it necessary to determine them individually for respective customer segments? The answering of these and other interesting questions can help to further develop and refine our approach. Second, while we were able to present a novel approach to account for customers' positive and negative social influence, we see the recognition and interpretation of social influence – whether positive or negative – in general as a very interesting field for future research. As discussed in our paper, sentiment analysis techniques are suitable to determine the parameters for our approach since the mere recognition of a connection between two customers can imply a wrong indication about the direction, strength, and polarity of the social influence exerted between them. On the one hand, studies supporting the negativity effect tend to reason that negative pieces of information are simply perceived as more attention grabbing and receive greater scrutiny in the process (Homer and Yoon 1992). On the other hand, studies supporting the positivity effect reason that positive messages strongly affect customers' judgment by enabling simple heuristic processing, while negative messages trigger more systematic information processing (Edwards and Edwards 2013). Hence, past research examining the relative effect of positive and negative social influence, i.e. positive and negative information, on customers' decision making processes, has actually produced controversial results, suggesting that the relative weight of positive and negative information may depend upon particular, so far, not thoroughly investigated conditions such as product type, a customer's prior consumption goals, or simply research design (Pentina et al. 2015). In addition to the pure recognition of positive or negative social influence based on sentiment analysis, the correct interpretation, the detection of sarcasm, and the classification of the relevance for the customers' revenue is also quite important and has to be considered for future research (Liu 2012; Vinodhini and Chandrasekaran 2012). Finally, the applicability of our approach relies on the availability of data about the online customer network (Kumar et al. 2010b). Therefore, the firm-sponsored online customer network must be able to collect sufficient data for the application of our proposed approach. With focus on the continuous implementation of our approach into a firm-sponsored online customer network, it might therefore be necessary to first establish a sufficient data basis regarding customers' interaction including the direction, strength, and polarity of exerted social influence.

Conclusion

Due to the ongoing proliferation of social technologies and the resulting increasing interconnectedness between customers in firm-sponsored online customer networks, it is no longer acceptable to regard customers as independent, uncross-linked, and separately acting individuals when evaluating their value contribution for the company (eMarketer 2017; Roberts and Dinger 2016). Due to the change of customers into active creators and publishers of information and opinions, the importance of customers' social influence on each other becomes more and more important both for research and practice (Adjei et al. 2010; Roberts and Dinger 2016; Scholz et al. 2013). Existing studies evaluate customers predominantly based on their positive social influence induced on other customers and disregard the destructive power of negative social influence (e.g., Däs et al. 2017; Heidemann et al. 2010; Nejad et al. 2014). Closing this research gap, we propose a novel approach to account for customers' positive as well as negative social influence in online customer networks. Our approach focuses thereby on the fact that there is a significant difference between customers who exert negative social influence and customers who exert positive social influence on other customers. We thereby extend existing research by considering direct and indirect as well as positive and negative social influence between customers. Furthermore, our approach avoids double counting of the network's overall sum of value contribution since customers' individual value contribution is reallocated based on positive and negative social influence exerted between them. Therefore, our approach allows practitioners to consider the destructive power of negative social influence and the enriching power of positive social influence on customers' purchase decisions. It is intended to support companies to identify customers' "true" integrated value contribution in the context of their online customer networks. Companies can therefore lay their focus on valuable customers and identify promising customers regarding their integrated value contribution. This allows for a more efficient allocation of marketing resources. We hope that our research contributes to a better understanding of positive and negative social influence in online customer networks and will serve as a proper starting point for future work on this exciting topic.

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