

Network-oriented Customer Valuation and Social Engagement Analysis in Online Customer Networks



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Georg Lindner
M. Sc. Wirtschaftsinformatik

Berichterstatter:
Prof. Dr. Bernd Heinrich
Prof. Dr. Mathias Klier

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List of Abbreviations

CLV	Customer lifetime value
ECIS	European Conference on Information Systems
ICIS	International Conference on Information Systems
IS	Information System
OSN	Online Social Networks
SNA	Social Network Analysis
VHB	Verband der Hochschullehrer für Betriebswirtschaft
WI	Wirtschaftsinformatik
WKWI	Wissenschaftliche Kommission für Wirtschaftsinformatik
WoM	Word-of-Mouth

1 Introduction

The introductory chapter includes a brief motivation and **presentation of the dissertation's** research topics. Furthermore, the research questions for each topic and the used research paradigms and approaches are presented. Finally, the structure of the dissertation is described.

1.1 Motivation

The ongoing development of the Internet in the last two decades has an increasing impact on society and business (Castells, 2010; Fuchs, 2017; Lupton, 2015). The digital revolution changed the way how, at which frequency, and at which speed people are communicating and interacting with each other (e.g., Dosi and Galambos, 2013; Fuchs, 2017; Valenduc and Vendramin, 2017). In 2018, the number of internet users will reach the 4 billion mark, which is more than 50% of the global population (e.g., Kemp, 2018). Among them, more than 3 billion people worldwide are already regarded as active social media users (e.g., eMarketer, 2018). The emergence of web 2.0 technologies had major consequences for the relationship between customers and companies. Web 2.0 has led to an increasing engagement of companies in online social networks (OSN) as well as to the establishment of firm-sponsored online customer networks (Benmiled-Cherif, 2015; eMarketer, 2018; Lenka et al., 2016; Zeng et al., 2010). The companies thereby aim at enhancing their knowledge **of customers' needs, preferences, and desires to increase customer-brand loyalty** in the long term (e.g., Ahmad and Laroche, 2017; Brogi, 2014; Hajli et al., 2017). An online customer network thus acts as a specialised online community for customers who want to share common social and commercial interests with other customers and interact with the sponsoring company (McAlexander et al., 2002; Porter, 2004; Zheng et al., 2015). Many of the top 100 global companies host their own online customer network (Brenner, 2017; Manchanda et al., 2015; Gilliland, 2017). Popular examples are the online customer networks of *Oracle*¹, *SAP*², or *Lego*³, where millions of customers are connected to share experiences about products and services, ask and answer company-related questions, and help each other with specific issues related to the company and its products (e.g., Hong, 2015). **Online customer networks display thereby the change of customers' role from traditional passive consumers towards creators and publishers of information, opinions, and emotions** (e.g., Di Gangi and Wasko, 2016; Lee, 2014; Roberts and Dinger, 2016). By using different forms of social engagement activities like the exchange of private messages, asking and answering product-related questions in public forums or rating products, customers

¹ <https://community.oracle.com/welcome>

² <http://scn.sap.com>

³ <http://ideas.lego.com>

can influence each other's purchase decisions (Faraj et al., 2015; Gummerus et al., 2012; van Doorn et al., 2010; Wirtz et al., 2013). Furthermore, from a sponsoring company's perspective, customers' social engagement activities in online customer networks allow enduring and emotional relationships not only between participating customers but also between customers and companies. Therefore, social engagement enables the establishment of a potential strategic competitive advantage in the form of increased brand awareness, established trust, and amplified customer loyalty (Barreda et al., 2015; Brodie et al., 2013; Dessart et al., 2015; Farzindar and Inkpen, 2016; Sashi, 2012; Wang et al., 2016; Weiyo et al., 2017). Sponsoring an online customer network, however, also poses a risk for companies as it requires a comparatively large initial investment for establishing the technical and organisational infrastructure. Companies also have to invest in marketing and public relations to increase customers' awareness for the online customer network. Therefore, companies are interested in identifying, whether an online customer network and customers' social engagement is beneficial for the company or not (e.g., Culnan et al., 2010; Gensler et al., 2013; Kaplan and Haenlein, 2010).

Word-of-Mouth (WoM) is an essential part of customers' social engagement activities and is seen as one of the most trustworthy forms of customer-to-customer interaction, thus relevant in the context of product recommendations (Ahmad and Laroche, 2017; Blazevic et al., 2013; Kozinets et al., 2010; Haenlein and Libai, 2017). Due to the growth of online customer networks, large amounts of WoM data is available and waiting for exploitation by the sponsoring companies (Farzindar and Inkpen, 2016). These data comprise forum posts and comments, questions and answers, public as well as private messages, and many more textual WoM-content generated by customers' social engagement activities. However, the large volume of data and its expensive analysis are major challenges for both researchers and practitioners. The research areas of text mining and sentiment analysis techniques provide a solution and are suitable for investigating vast amounts of user-generated content-based data on customers' social engagement in online customer networks (Kumar and Sebastian, 2012; Liu, 2012; Pang and Lee, 2008; Pozzi et al., 2016). These techniques allow the determination of positive, negative, or neutral polarity, the direction as well the strength of social influence of customers' social engagement activities (Chilhare and Londhe, 2016; Gamon et al., 2005; Liu, 2017; Nitzan and Libai, 2011).

Research on online customer networks has grown in parallel with the increasing practical importance of OSN for companies (Goodwin, 2014; Lee, 2014; Zhang et al., 2017). Therefore, customers' social engagement in a company's online customer network is generally seen as strategically important for future business success by means of increased customer loyalty, enhanced esteem of the existing portfolio, and improved adaption rates for new products (Brodie et al., 2013; Fournier and Lee, 2009; Hollebeek et al., 2016; Thompson and Sinha, 2008). Recent studies started to examine the linkage between customers' social

engagement and customer profitability in online customer networks (Algesheimer et al., 2010; Algesheimer et al., 2005; Goh et al., 2013; Rishika et al., 2013; Zhu et al., 2012). Other researchers conducted one of the first comprehensive studies about economic effects of online customer network membership and participation (Manchanda et al., 2015). However, little is known in-depth about the relationship between social engagement and customer profitability, for example, whether online customer networks are economically beneficial and if so, which types of social engagement activities influence the value of different kinds of customers (Bateman et al., 2011; Casaló et al., 2010a; Goodwin, 2014). Research acknowledges in general that different types of social engagement lead to different user behaviours (e.g., Bateman et al., 2011). However, there is a lack of knowledge about the **effect of different types of social engagement on customers' revenues**. This also accounts for the research on sentiment analysis and text mining in the context of online customer networks (Aggarwal and Zhai, 2012; Cambria et al., 2017; Liu, 2012). Despite recent efforts to analyse the sentiment in OSN, little is known about the content-related influence of **customers' social engagement activities on their purchase behaviour**. Therefore, a practical application of sentiment analysis in order to investigate the polarity (positive, neutral, or **negative sentiment**) of **customers' social engagement activities in online customer networks** is desirable as well as **in-depth analyses of the relationship between customers' sentiment and their revenues** (Gonçalves et al., 2013; Liu, 2012).

By acknowledging the importance of customers' social engagement activities and their influence on customers' purchase decisions, companies have recognized the necessity of understanding the actual impact of customers' social influence exerted within an online customer network. Customers' mutual social influence is analysed on an individual level in order to identify influential and important customers. Thereby, a differentiation takes place **between a customer's own value contribution in the form of their purchases and a customer's social influence, with which they influence others' purchase decisions** (e.g., Goldenberg et al., 2009; Heidemann et al., 2010; Kiss and Bichler, 2008; Nejad et al., 2014). Social influence is not exclusively positive but can also have a negative impact on the purchase decisions of influenced customers (e.g., Kumar et al., 2010a; Weinberg and Davis, 2005). In fact, positive and negative social influence exerted between customers in the context of a firm-sponsored online customer network have to be considered quite differently **by the company when calculating customers' value contribution** (e.g., Ballantine and Au Yeung, 2015; Pang and Lee, 2008).

Against this background, the dissertation focuses on the two complementary research topics "Social Engagement and Customer Profitability" (Topic 1) and "Network-Oriented Customer Valuation" (Topic 2), as displayed in Figure 1.

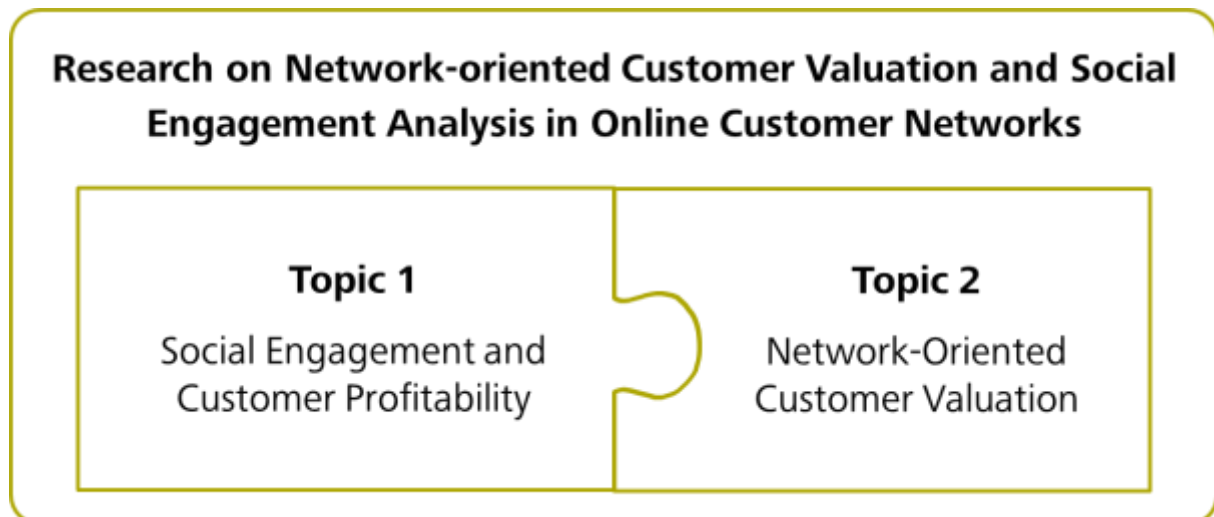


Figure 1. Overview of the dissertation's research topics.

In Topic 1, the dissertation focuses on investigating the relationship between social engagement and profitability of customers participating in firm-sponsored online customer networks (e.g., Algesheimer et al., 2010; Manchanda et al., 2015). Furthermore, the influence of different types of social engagement activities as well as the polarity of customers' social engagement activities are the focus of this research topic (e.g., Brodie et al., 2013; Faraj et al., 2015; Liu, 2017). The findings aim at supporting researchers and practitioners alike to better identify and characterize potentially valuable customers within an online customer network. Furthermore, by investigating the varying influence of different types of social engagement activities, the identification of more beneficial social engagement activities is supported. With the help of text mining and sentiment analysis techniques, the content of customers' social engagement activities is determined (e.g., Farzindar and Inkpen, 2016; Liu, 2012). Based on this research, the dissertation aims in the context of this research topic at broadening the understanding and knowledge of customers' social engagement activities in firm-sponsored online customer networks.

In Topic 2, the dissertation develops novel customer valuation approaches incorporating direct as well as indirect positive social influence exerted between customers participating in online customer networks. However, beside not only positive social influence but also negative social influence, for example in the form of negative WoM, has to be considered when calculating a network-oriented customer value. Therefore, this dissertation further develops an integrated approach in the context of this research topic to calculate a network-oriented customer value, including both positive and negative social influence exerted between customers participating in online customer networks. Negative social influence thereby can result in a lost value contribution, hence, a customer's value contribution which is not realized due to the negative social influence of other customers on the purchase decision of a specific customer.

1.2 Research Questions

Based on the motivation above, the aim of this dissertation is to contribute to research on social engagement and customer profitability (Topic 1) and network-oriented customer valuation (Topic 2).

The dissertation expands in Topic 1 existing research on the relationship between customers' social engagement in online customer networks and their customer profitability. The ongoing growth of firm-sponsored online customer networks within the last few decades has led to a large share of customers using these networks for the exchange of information about a company's products and services (e.g., Algesheimer et al., 2010; eMarketer, 2018). Customers' social engagement in online customer networks is generally seen as strategically important for future business success since digitally connected customers are viewed as having a great impact on customer profitability and therefore on the long-term business success of companies. Social engagement describes the form of customer participation and interaction within an online customer network in the form of social engagement activities like posting, commenting, or asking and answering questions (e.g., Casaló et al., 2010b). Although existing literature started to investigate the economic effects of online customer networks, there is a lack of in-depth analyses of the relationship between customers' social engagement and their customer profitability (Algesheimer et al., 2010; Goh et al., 2013; Manchanda et al., 2015; Zhu et al., 2012).

In the context of this dissertation, customer profitability refers to customers' revenues regarding the purchase of financial products. Summed up, for a sponsoring company, it is not clear which participating customers are actually valuable regarding their social engagement in the company's online customer network. Additionally, there is little knowledge about which kind of customers' social engagement is more valuable for the company. Further, the impact of the polarity of customers' social engagement activity has not been investigated in detail. For example, whether social engagement activities with a positive polarity also positively influence other customer's purchase behaviour and vice versa.

Therefore, this dissertation addresses the research on Topic 1 with the following research questions:

- RQ.1: *How is the relationship between customers' social engagement and customer profitability in online customer networks?*
- RQ.2: *How is the purchase behaviour affected by different forms of customers' social engagement?*
- RQ.3: *How are revenues influenced by the polarity of customers' social engagement activities?*

In the context of Topic 2, the dissertation focuses on broadening the research on network-oriented customer valuation. Since customers nowadays are increasingly digitally connected

and interact with each other extensively via media like online customer networks, social marketing and digital commerce are seen as the top areas of future technology investment by marketers (Genovese et al., 2015; Kumar et al., 2016; McCarthy et al., 2014). One major challenge for companies is to consider customers' mutual direct and indirect social influence on their purchase decisions, for example in the form of WoM (Gruner and Power, 2018; Nunes et al., 2018; Teng et al., 2014). It is insufficient to view customers in isolation and value them without considering both positive and negative network-related effects, since this might lead to an under or overestimation of influencing customers and an over or underestimation of influenced customers. Furthermore, negative social influence, for example through negative WoM, may result in cash flow potential that cannot be realized. For marketers this means a big impact on the valuation of customers in the context of network effects and therefore the effective allocation of marketing efforts. Network effects are defined as direct and indirect social influence exerted between customers in the context of online customer networks (e.g., Weinberg and Berger, 2011). Customers are thereby influencing each other indirectly when customers, who have been influenced by another customer, again influence other customers. This is also known as the "ripple effect" (e.g., Oestreicher-Singer et al., 2013).

By neglecting positive or negative effects, traditional customer valuation models – like for example the CLV (Berger and Nasr, 1998) – might lead to a misallocation of resources (Heidemann et al., 2010; Weinberg and Berger, 2011). Recent research has proposed novel approaches for network-oriented customer valuation. However, most of these approaches are subject to limitations like double counting or valuation errors and only take direct social influence among customers into regard (Kumar et al., 2010a; Kumar et al., 2010b; Libai et al., 2013; Oestreicher-Singer et al., 2013). The dissertation therefore aims at developing novel customer valuation approaches by considering positive but also negative network effects due to mutual social influence among customers. In the context of Topic 2, the dissertation addresses the following research questions:

- RQ.4: *How can direct and indirect network effects be integrated into customer valuation?*
- RQ.5: *How can negative social influence among customers be integrated into an existing customer lifetime network value model?*

Figure 2 provides an overview of Topic 1 and Topic 2 and the according research questions RQ.1 – RQ.5.

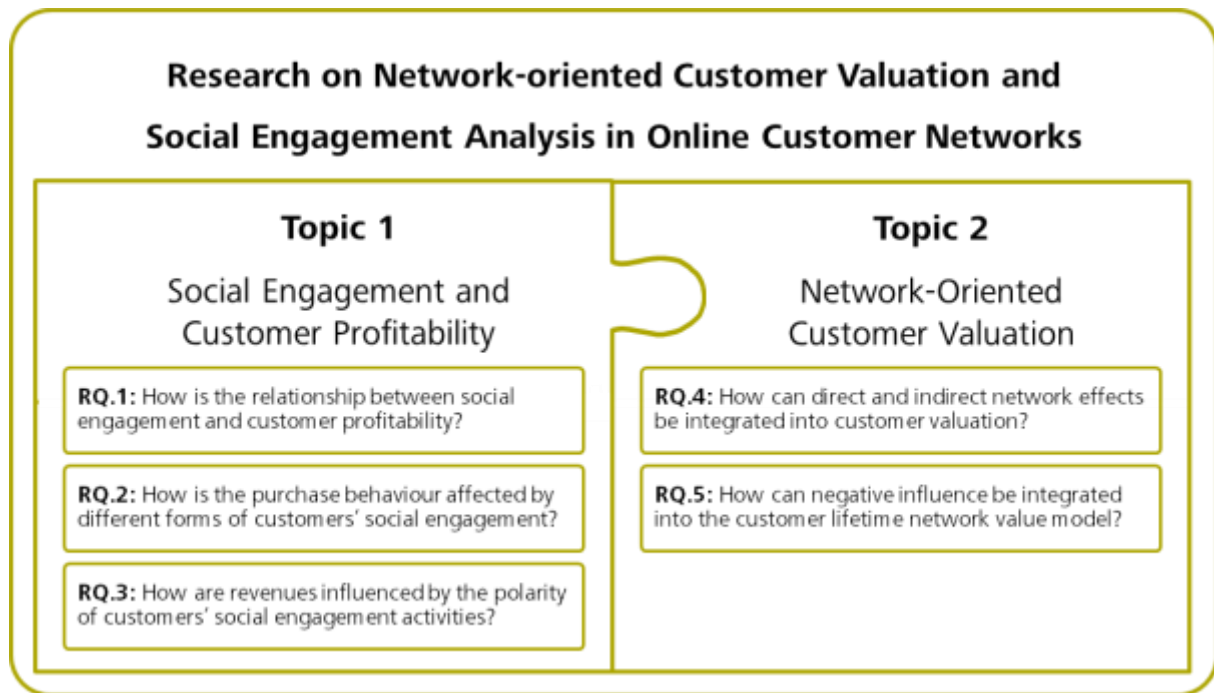


Figure 2. Overview of the *dissertation's* research questions.

Table 1 provides an overview of the research questions for each research topic and which research paper addresses which research question.

Research Topic	Research Question	Research Paper
Topic 1: Social Engagement and Customer Profitability	RQ.1: How is the relationship between social engagement and customer profitability?	<i>Social Engagement and Customer Profitability in Online Customer Networks</i>
	RQ.2: How is the purchase behaviour affected by different forms of customers' social engagement?	<i>The Impact of Social Engagement on Customer Profitability - Insights from a Direct Banking Institution's Online Customer Network</i>
	RQ.3: How are revenues influenced by the polarity of customers' social engagement activities?	<i>The Hidden Moods of Customers - Analysing the Sentiment of Customers' Social Engagement Activities in a firm-sponsored Online Customer Network</i>
Topic 2: Network-Oriented Customer Valuation	RQ.4: How can direct and indirect network effects be integrated into customer valuation?	<i>Customer Lifetime Network Value: Customer Valuation in the Context of Network Effect</i>
	RQ.5: How can negative influence be integrated into the customer lifetime network value model?	<i>Influence Makes or Breaks Your Brand's Success Story – Quantify Positive and Negative Social Influence in Online Customer Networks</i>

Table 1. Overview of the *dissertation's* research questions and papers.

1.3 Research Approach

To investigate the research questions of Topic 1 and Topic 2, the established research paradigms of behavioural and design science are applied in this dissertation (Gregor and Hevner, 2013; Hevner et al., 2004; Peffers et al., 2007). While behavioural science develops and justifies theories that explain human behaviour in organizations in combination with information systems, design science provides solutions to problems in the context of information systems by developing and evaluating artifacts, like models, methods, or instantiations (e.g., Gregor and Hevner, 2013). Due to the diverse research questions in both topics, this dissertation includes both research paradigms.

The research questions of Topic 1 are addressed following the behavioural science paradigm by examining the online customer network of an innovative German direct banking institution. Since its online customer network with more than 500,000 registered users is regarded as a major competitive advantage against established traditional financial banking institutions, it is well suited for the investigation of its customers' social engagement activities and the relationship with their customer profitability (Begemann et al., 2015; Eismann, 2015; Kröner, 2017). For RQ.1, the dataset consists on the one hand of customer revenue data regarding a recently launched bank capital bond, which represents customer profitability in the context of RQ.1. On the other hand, the dataset provides customers' social engagement data of around 2,000 users of the online customer network in the form of number of group memberships, number of written posts, and the duration of group membership. To investigate the relationship between social engagement and customer profitability in the online customer network, Social Network Analysis (SNA) is applied, which is intensively used in Information System (IS) research to study the structure of networks and the relationships between its members (Kane et al., 2014; Scott, 2013; Wasserman and Faust, 1994). In fact, an online customer network can be represented as a graph with nodes and directed and weighted ties between these nodes (Barrat et al., 2004). In this context, there exist several SNA measures to quantify the centrality of nodes and therefore to identify important customers within an online customer network like closeness centrality, betweenness centrality, degree centrality, and eigenvector centrality (Bonacich, 1972; Freeman, 1979; Wasserman and Faust, 1994). Based on the calculation of the centrality measures using the *igraph*⁴ package for R, the customers were classified depending on their centrality scores for each measure and categorized into four equally large social engagement categories. Statistical tests (e.g., chi-squared test (Greenwood and Nikulin, 1996)) were used to characterize the individual customer's position within the online customer network. Based on a left-tailed, two-sample t-test for unequal sample sizes and unequal variances, significance differences between customers who have purchased the financial product and customers who have

⁴ igraph.org/r/

not were identified. The analysis of RQ.1 provides novel insights about the relationship between customers' social engagement and customer profitability in online customer networks. Building on these findings, the research on RQ.2 uses an extended and comprehensive dataset including sales data of credit cards of more than 100,000 customers, social engagement activities of all active customers of the direct banking institution's online customer network as well as basic demographic information like age and place of residence about each customer. Based on a multiple linear regression model, different forms of customers' social engagement activities in combination with customer profitability were investigated in-depth (Cohen et al., 2003). Multiple linear regression is the most common form of linear regression analysis and commonly used to explain the relationship between one dependent variable and two or more independent variables (Yan and Su, 2009). Due to the uniqueness of the available dataset, a comprehensive analysis of the relationship between social engagement and customer profitability as well as purchase behaviour is possible. Finally, the research on RQ.3 further extends the existing research on customers' social engagement in online customer networks by analysing the sentiment of social engagement activities as well as the relationship between customers' sentiment and their revenues. Based on data of more than 5,000 active users during the time period of observation, the sentiments of around 75,000 social engagement activities (e.g., a comment in a forum group) were analysed using an unsupervised lexicon-based approach (Pang and Lee, 2008; Pozzi et al., 2016; Turney, 2002; Vohra and Teraiya, 2013). Each word within a social engagement activity is compared to a given sentiment lexicon and the corresponding sentiment value is added to the overall sentiment value of the document (e.g., Annett and Kondrak, 2008). Customers' social engagement activities can be divided into initial social engagement activities and reactions to them. Based on a chi-square test of independence (e.g., Agresti, 2007), the differences between the sentiment of customers initial social engagement activities and the reactions of other customers to them are analysed. Finally, an overall sentiment score is calculated to investigate the relationship between customers' sentiment and their revenues. The sentiment score represents the sum of all positive minus the sum of all negatively labelled entities attributed to the individual customer (e.g., Annett and Kondrak, 2008; Collomb et al., 2014; Ferrara and Yang, 2015). Summed up, sentiment analysis in the context of online customer networks is an effective method to analyse the increasing amount of customer data occurring on a daily basis (e.g., Liu, 2012).

The research questions of Topic 2 are addressed following the design science paradigm. The aim of the design-oriented approach in context of RQ.4 is the development of a novel model for customer valuation by integrating individual purchase expenditures as well as network effects in the form of direct and indirect positive social influence among customers within an online customer network. The applicability and relevance of the model is demonstrated using a real-world dataset of a European OSN focusing on sports (Peffer et al.,

2007). With data both from user interactions within the OSN and customers' buying behaviour in the affiliated online shop, the difference to traditional customer valuation approaches and customer valuation models considering only partial network-related aspects is analysed. Based on this newly designed customer valuation model, RQ.5 further addresses the development of a network-related approach by including not only direct and indirect positive but also negative social influence. The approach focuses on the fact that there is a significant difference between customers who exert positive social influence in contrast to customers who exert negative social influence on other customers. The applicability and relevance of the novel customer valuation model accounting for both direct and indirect positive and negative social influence is demonstrated by means of an illustrative online customer network.

Table 2 gives an overview of the addressed paradigm, the research approaches, and the used data for each research questions in the context of this dissertation.

Research Topic	Research Question	Paradigm	Research Approach	Data
Topic 1: Social Engagement and Customer Profitability	RQ.1: How is the relationship between social engagement and customer profitability?	Behavioural science	SNA, statistical tests	Company-owned data
	RQ.2: How is the purchase behaviour affected by different forms of customers' social engagement?	Behavioural science	Regression model, statistical tests	Company-owned data
	RQ.3: How are revenues influenced by the polarity of customers' social engagement activities?	Behavioural science	Sentiment analysis, statistical tests	Company-owned data
Topic 2: Network-Oriented Customer Valuation	RQ.4: How can direct and indirect network effects be integrated into customer valuation?	Design science	Analytical model, case study evaluation	Company-owned data
	RQ.5: How can negative influence be integrated into the customer lifetime network value model?	Design science	Analytical model, case study evaluation	Demonstration data

Table 2. Overview of the dissertation's research approaches.

1.4 Structure of the Dissertation

As displayed in Figure 3, the dissertation is structured into four main chapters: In the first chapter, a brief motivational introduction to the dissertation is followed by the introduction of the research topics, research questions as well as research approaches. In the second chapter, Topic 1 with its focus on social engagement and customer profitability is presented. The third chapter presents the research on network-oriented customer valuation in the context of Topic 2. Finally, in the fourth chapter, the dissertation ends with a summary of the main findings and limitations as well as future research perspectives.

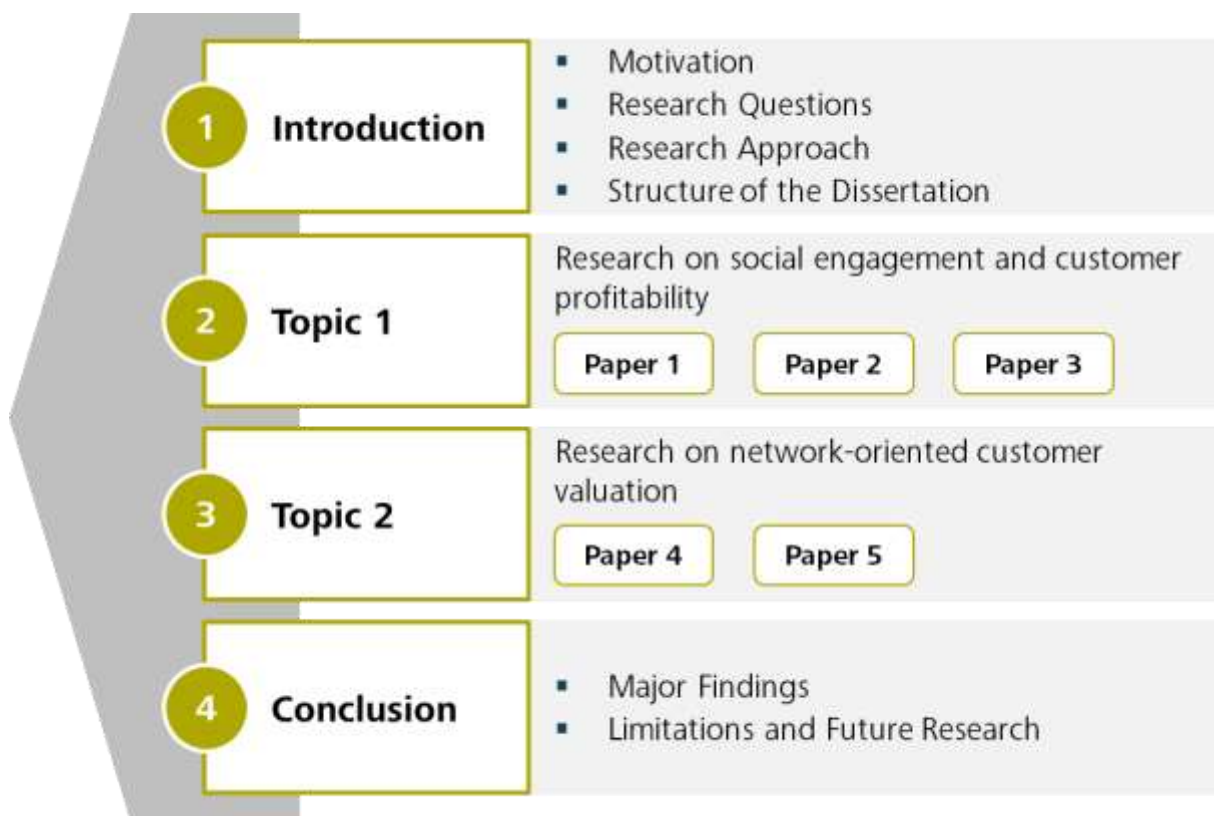


Figure 3. Overview of the structure of the dissertation.

Table 3 provides an overview of the dissertation's research papers. For each research paper, the title, the participating author(s), the publication medium, the year of publication, the ranking according to VHB⁵, and the status of the paper at the time of the submission of the dissertation are displayed.

⁵ Ranking according to VHB-JOURQUAL 3 (conducted in 2015): <http://vhbonline.org/vhb4you/jourqual/vhb-jourqual-3>

No.	Title	Author(s)	Publication medium	Year	Ranking VHB	Status
1	Social Engagement and Customer Profitability in Online Customer Networks	Julia Klier Mathias Klier Georg Lindner	Proceedings of the 24 th European Conference on Information Systems (ECIS)	2016	B	Accepted
2	The Impact of Social Engagement on Customer Profitability - Insights from a Direct Banking Institution's Online Customer Network	Annette Felgenhauer Julia Klier Mathias Klier Georg Lindner	Proceedings of the 25 th European Conference on Information Systems (ECIS)	2017	B	Accepted
3	The Hidden Moods of Customers - Analysing the Sentiment of Customers' Social Engagement Activities in a firm-sponsored Online Customer Network	Georg Lindner	Proceedings of the 14 th International Conference on Wirtschaftsinformatik (WI)	2019	C	Submitted (<i>under review</i>)
4	Customer Lifetime Network Value: Customer Valuation in the Context of Network Effect	Miriam Däs Julia Klier Mathias Klier Georg Lindner Lea Thiel	Electronic Markets 27 (4)	2017	B	Accepted
5	Influence Makes or Breaks Your Brand's Success Story – Quantify Positive and Negative Social Influence in Online Customer Networks	Catherine Baethge Julia Klier Mathias Klier Georg Lindner	Proceedings of the 38 th International Conference on Information Systems (ICIS)	2017	A	Accepted

Table 3. Overview of the dissertation's research papers.

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2 Social Engagement and Customer Profitability

This chapter addresses with Topic 1 and the according research questions RQ.1 – 3 the first part of the dissertation. The first paper, published in the proceedings of the 2016 European Conference on Information Systems, analyses thereby the relationship between social engagement of customers participating in online customer networks and their customer profitability (RQ.1). Building on it, the second paper, published in the proceedings of the 2017 European Conference on Information Systems, investigates **in-depth customers' purchase** behaviour in relationship to different types of social engagement (RQ.2). The final paper for Topic 1 which is submitted to the 2019 Conference on Wirtschaftsinformatik focuses on the analysis of the sentiment of **customers' social engagement activities and their revenues** (RQ.3). Together, the paper presented in this chapter analyse in detail the relationship between social engagement activities and profitability of customers participating in a firm-sponsored online customer network.

2.1 Social Engagement and Customer Profitability in Online Customer Networks

No.	Title	Full Citation	Year	Status
1	Social Engagement and Customer Profitability in Online Customer Networks	Klier, J., M. Klier and G. Lindner (2016). "Social Engagement and Customer Profitability in Online Customer Networks". In: <i>Proceedings of the 24th European Conference on Information Systems (ECIS), Istanbul, Turkey.</i>	2016	Accepted

Abstract

The rapid growth of the Internet has led to a revolution in the relationship between customers and companies. After the first experiences on social media platforms, companies started hosting their own online customer networks where formerly passive consuming customers are able to connect, share, and cooperate with each other and the company. This social engagement of customers is generally considered as an incredible value for the hosting company. However, while previous research regularly takes a positive relationship between users' social engagement and customer profitability in online customer networks for granted, there is still a lack of research rigorously analyzing this aspect in detail. Against this background, the aim of our paper is to provide an in-depth investigation of the relationship between users' social engagement and customer profitability in online customer networks using a unique dataset of a German direct banking institution. This leads to interesting results that do not support either existing statements in literature or best current practices. Indeed, in our case we do not generally observe significant higher social engagement for "buyers" compared with "non-buyers".

Keywords: Online Customer Network, Social Engagement, Customer Profitability, Social Network Analysis.

1 Introduction

Within less than 20 years the world became a digital networked community, from 1% of the world population with access to the Internet in 1995 up to 40% in 2014 (Internet Live Stats, 2015). A large share of the people worldwide use online social networks for socialising, entertainment, information, and business (Ipsos, 2013; National Opinion Research Center et al., 2015). The rapid shift from analogue to digital society has major impact on the relationship between customers and companies, resulting amongst others, in the companies' increasing engagement in social media (Rishika et al., 2013). Growing interaction and networking of customers in the digital world have also fostered a rapid development towards firm-sponsored online customer networks (Belk and Tumbat, 2005; Algesheimer et al., 2010). An online customer network represents an online community of customers, whose members share similar social and commercial interests and are therefore likely to exhibit similar characteristics in terms of cognitive, emotional, or material resources (McAlexander et al., 2002). According to Manchanda et al. (2015), up to 50% of the top 100 global companies like *Disney*, *Procter & Gamble*, or *Amazon* host their own online customer network. The *SAP Community Network*¹ where customers can maintain a personal profile, establish friendship ties, and interact and exchange with other customers via discussion groups or direct messages may serve as a popular example. Online customer networks are generally seen to create substantial value for all parties involved: for example information retrieval for participating customers, knowledge collaboration between customers, and customer retention for sponsoring companies (cf. e.g., Faraj et al., 2011; Wirtz et al., 2013). Therefore, it is not surprising that companies have a strong interest in establishing and developing online customer networks in order to take advantage of these benefits (Agarwal et al., 2008; Baldus et al., 2015).

Previous research already started to investigate the economic effects of online customer networks (cf. Algesheimer et al., 2010; Zhu et al., 2012; Manchanda et al., 2015). However, to this date, little is known in depth about the relationship between customers' social engagement and customer profitability in online customer networks. Indeed, so far it is not clear whether firm-sponsored online customer networks are economically beneficial and if so, what kind of members of these networks are particularly valuable for the company (cf. e.g., Goodwin, 2014). Against this background, the aim of our paper is to provide an in-depth investigation of the relationship between customers' social engagement and customer profitability in online customer networks using a dataset of a German direct banking institution's online customer network. The dataset contains unique information regarding the customers' social engagement and their financial data. Based on Social Network Analysis (cf. e.g., Scott, 2013), we derive interesting findings that do not support either existing

¹ <http://scn.sap.com>

statements in literature or best current practices. Indeed, we observe that “*buyers*” are not generally characterized by significant higher social engagement in the online customer network compared with “*non-buyers*”.

The remainder of this paper is organized as follows: In Section 2, we briefly review the theoretical foundations and the related literature. In Section 3, we describe the research methodology and the dataset of the German direct banking institution which serves as a basis for our work. In Section 4, we present our findings derived based on Social Network Analysis. In Section 5, we discuss implications for theory and practice, critically reflect on limitations, and provide directions for further research. Finally, we conclude with a brief summary of our results.

2 Theoretical Background

2.1 Social engagement in online customer networks

The impact of social media on the customer-firm relationship has led to an increasing importance of online customer networks (Manchanda et al., 2015). An online customer network is a specialised, non-geographically bound platform for users who share the same interests in a company’s products and services and who want to interact with each other and with the company (Muniz and O’Guinn, 2001; McAlexander et al., 2002; Porter, 2004). With firm-sponsored online customer networks (Kannan et al., 2000; Porter and Donthu, 2008), firms aim to strive economic benefits (Balasubramanian and Mahajan, 2001). Actually, it is assumed that firm-sponsored online customer networks will become increasingly important for companies (cf. e.g., Lee, 2014; Goodwin, 2014). According to Wirtz et al. (2013), customers have an intrinsic motivation to participate actively in online customer networks. This motivation is due to the reputation associated with the company (e.g., Algesheimer et al., 2005; Hughes and Ahearne, 2010), social benefits, such as support from other members (e.g., Muniz and O’Guinn, 2001; Mathwick et al., 2008; Dholakia et al., 2009), and mere functional drivers like the reduction of uncertainty (e.g., Weiss et al., 2008; Adjei et al., 2010), a better information quality (e.g., Muniz and O’Guinn, 2001; Porter and Donthu, 2008), or monetary incentives (e.g., Garnefeld et al., 2012). In general, online customer networks help customers to interact with likeminded who share the same interest and passion in a specific brand, service, or product (McAlexander et al., 2002).

Research on social engagement of customers is a fairly young field of science (van Doorn et al., 2010) and grew in parallel with the increasing emergence of online customer networks (cf. e.g., Libai, 2011; Sashi, 2012). Nonetheless, social engagement of customers is regarded as a key element of online customer networks (e.g., Brodie et al., 2013). According to Coulter et al. (2012), it includes, but is not limited to, discussions, relationship building, com-

menting, knowledge acquisition, and opinion forming, hence the sum of all human communication and interaction through online customer networks and other social media (van Doorn et al., 2010). Among the basic aspects of social engagement are the level of customer participation and interaction within the network (cf. e.g., Algesheimer et al., 2005; Bagozzi and Dholakia, 2006; Casaló et al., 2010), the quality of relationships as expressed by satisfaction and personal gain (cf. e.g., Adjei et al., 2010; Casaló et al., 2010), the degree of identification with the online customer network (cf. e.g., Algesheimer et al., 2010; Casaló et al., 2010), and the quality of communication (cf. Adjei et al., 2010). In literature, another **differentiation of social engagement is between the dimensions valence, i.e. if customers' social engagement has positive or negative consequences for the company (e.g., Brady et al., 2006), modality and form of the expressed social engagement, the temporal and geographic scope of social engagement, the potential impact, and the customers' plans and goals (van Doorn et al., 2010). Therefore, social engagement is regarded as the company's possibility to establish enduring and emotional relationships towards their customers (cf. e.g., Sashi, 2012). Brodie et al. (2011) further differentiate between affective, cognitive, and behavioural engagement. Affective engagement covers the emotions experienced in an online customer network. Cognitive engagement describes the level of attention and absorption focused on an online customer network. Behavioural engagement, mainly occurring in discussion groups, includes to share experiences, ideas, and other content (cf. Vivek et al., 2014), to learn from other network participants (cf. Dholakia et al., 2004; Zaglia, 2013), and to recommend products, services, or network content to other users (e.g., Schau et al., 2009). In summary, in an online customer network social engagement of customers can strengthen the bond between customers and company and increase customer loyalty towards the company (cf. e.g., McAlexander et al., 2002; Kumar et al., 2010; Dessart et al., 2015).**

2.2 Social engagement and customer profitability in online customer networks

A dedicated social engagement of customers in a company's online customer network is widely seen as strategically important in order to establish a competitive advantage and as a foundation for future business success (Brodie et al., 2013). Companies furthermore expect a stronger bond and an increase in customer loyalty (cf. e.g., Hagel and Armstrong, 1997; Bagozzi and Dholakia, 2006; Fournier and Lee, 2009). This, in turn, enhances the ability to understand customers (cf. e.g., Williams and Cothrel, 2000), increases the esteem of the existing portfolio (cf. e.g., McAlexander et al., 2002), and improves the adoption rate for new products and services (cf. e.g., McAlexander et al., 2002; Thompson and Sinha, 2008). Regarding these benefits, it seems likely that social engagement in online customer networks is a primary driver of growth in sales and profitability (Voyles, 2007).

As social engagement may impact customer profitability, recent studies have started to examine different aspects regarding the link between social engagement in online customer networks and financial benefits. Among the first studies are Algesheimer et al. (2005), who **built up a conceptual model regarding the influence on customers' intentions and behaviours** in the context of an online customer network of a European car club. Their survey revealed a link between network membership and increased purchase intentions among customers. Although there was no direct link between social engagement and customer profitability, the research was the basis for a subsequent field study conducted by Algesheimer et al. (2010). This study examines the online customer network of eBay Germany, **regarding the impact of customers' network participation on their buying and selling behaviour**. Even though there was neither an in-depth analysis of the network participation nor of customer characteristics, the study revealed effects of the online customer network **on the bidding and selling behaviour of eBay's customers**. Because these effects were both positive and negative for the sponsoring internet auctioneer, Zhu et al. (2012) complemented the existing research on eBay with information of the lending platform Prosper.com **to focus on customers' risk-seeking tendencies** regarding their financial decisions. The study concluded that both active online customer network participation as well as establishing strong friendship ties within the network increase the willingness to take financial risks.

In order to better understand the impact of social engagement on customers purchase intentions, researchers focused on customers participating on a company's online social network platform (Kim and Ko, 2012; Goh et al., 2013). The results of the survey among luxury brand customers by Kim and Ko (2012) indicate a positive influence of social media activities on customers purchase intentions and therefore increasing future profits for the company. Goh et al. (2013) focused on the impact of social media content, both from customers and marketers, on customers' purchase expenditures. Therefore, the authors manually matched content data from an Asian retailer's Facebook fan page with consumer transaction data and came to the conclusion that social media content affects consumer purchase behaviour and leads to an increase in purchase expenditures. Rather than focusing on the content, Rishika et al. (2013) examined the effect of customers' level of participation on a wine retailer's social media fan page to investigate the impact on the customer lifetime value. The authors' main findings refer to an increase in customer profitability after the launch of a social media fan page for a treatment group as well as the fact that customers with high social media participation are more profitable than customers that do not participate strongly. Although the economic impact of social media participation of customers is examined, the study limits its definition of social engagement to the visit frequency of the company's social media sites and the observed economic effects are only seen from the perspective of an entire group of customers. Neither the social engagement of customers, nor the respective individual value proposition is examined in detail.

Recently, Manchanda et al. (2015) conducted a first comprehensive study with a long term examination of the economic effects of online customer network membership and participation. They analysed the impact of a newly launched online customer network on its members' purchase behaviour. Customer data was compared before and after the launch of the online customer network and tested in comparison with a non-participating control group. Manchanda et al. (2015) found a significant increase in customer expenditures attributable to customers joining the company's online customer network. The study based on data from a multi-channel entertainment and informational media retailer also reveals that both quantity and quality of interaction between customers of an online customer network have a positive economic impact for the operating company.

2.3 Research gap and theoretical contribution

Meanwhile, there is a well-established research stream on online customer networks. However, to this date, there is still a lack of knowledge with respect to a deep understanding of the relationship between users' social engagement in these networks and customer profitability. Indeed, only quite a few studies started to examine the financial implications of customers' participation in online customer networks. Some of these studies, due to reasons of data availability, lack a direct linkage of customers' social engagement data and corresponding financial data. Hence, the findings are either based on indirect deduction of potential online customer network influence on customer profitability by investigating customer intentions and behaviours (Algesheimer et al., 2005), survey based estimations of customer lifetime values (Kim and Ko, 2012), or complex (indirect) linking of data from general social media fan page visitors and financial data (Goh et al., 2013; Rishika et al., 2013). Other studies examine customers' buying and selling (Algesheimer et al., 2010) or financial risk behaviour (Zhu et al., 2012) in the context of online auction and lending platforms but do not focus on customer profitability. Finally, many researchers analyse data from third-party social media platforms (Kim and Ko, 2012; Goh et al., 2013; Rishika et al., 2013) and therefore lack the focus on online customer networks in the proper sense. In sum, to the best of our knowledge to date the study by Manchanda et al. (2015) is the only one, which analyses direct financial effects of a membership in an online customer network. Although this study is limited to participants in an offline and online loyalty program and lacks the focus on individual customers' network characteristics (e.g. customers' centrality and integration in the network), we regard this research as complementary to the findings of our work.

Our findings are based on the analysis of a unique dataset of the online customer network of a German direct banking institution. The dataset contains information regarding customers' social engagement in the online customer network and customers' financial transactions. Therefore, unlike previous studies, we are able to analyse the relationship between

users' social engagement and customer profitability in the online customer network by directly linking both customers' social and financial transaction activities. Hence, we do not have to rely on auxiliary constructs or estimated values. Further, we are able to characterize **the company's customers with respect to their social engagement and profitability**. In sum, our contribution to the existing body of knowledge in the research stream on online customer networks is twofold: our research provides (1) first insights regarding the interplay between social engagement and customer profitability based on a unique data set from an online customer network which also allows (2) a characterization of profitable and non-profitable customers with respect to their social engagement in the online customer network.

2 Research Method

2.1 Setting

To examine the relationship between social engagement and customer profitability in online customer networks, we have chosen the online customer network of a German direct banking institution. Founded in 2009, the direct banking institution offers a wide range of traditional as well as innovative financial products and financial services such as crowd investing or social payment and hosts one of the most active and innovative financial online customer networks in Germany. By providing an online customer network for its users to share, cooperate, and collaborate, the philosophy of the banking institution with around 100 employees is clearly built on the social engagement principles of Web 2.0 (cf. e.g., Constantinides and Fountain, 2008). Therefore, the online customer network is the key element of the direct banking institution's **business activities and serves as a major differentiating factor** over established traditional financial banking institutions which are often associated with non-transparency and information asymmetry (cf. e.g., Begemann, 2015).

The online customer network's **more than 300,000 registered users can express their social engagement** in various ways. Besides maintaining contacts and exchanging private messages via personal profile pages, they can also access and share evaluations about financial products and financial advisers. The agile core of the online customer network is, however, **users' social engagement in numerous public discussion groups debating about various financial topics**. Users who signed up for a membership in a discussion group can write, read, and like posts. The banking institution uses the discussion groups as main point of contact with their customers. In exchange with the banking institution customers are for example able to co-determine interest rates for loans or to recommend new banking products and banking services. For every user, a publicly visible and continuously updated community **measure is generated representing the individual user's social engagement within the online customer network**.

In sum, about one third of the registered users of the online customer network are at the **same time customers of the banking institution, purchasing the banking institution's financial products and using its financial services via an online banking platform directly connected with the online customer network.** Regarding our research focus, the online customer network is therefore ideally suited to examine the relationship between social engagement and customer profitability.

2.2 Data collection and preparation

To analyse the relationship between social engagement in the online customer network and customer profitability, the direct banking institution provided us with a dataset ranging from June 2014 to October 2015 consisting of two parts. The first part, which is used to represent customer profitability, **refers to the customers' revenues regarding a recently launched bank capital bond.** This financial product was on the one hand chosen because **of the lively discussions it caused in the direct banking institution's online customer network** around its initial launch. On the other hand, the characteristics of the product seem eminently suitable to examine the relationship between social engagement and customer profitability. The bank capital bond is available and of potential interest for every customer but it is at the same time not a daily used financial product, like for example a giro transfer. Therefore, it is neither restricted to a specific clientele nor used by the broad mass of customers without further thinking about its usage. Customers who purchase this financial product want to be informed about this product and one important source of information is the opinion and advice of other users in the online customer network. During the observation period 89 customers made 182 financial transactions of the bank capital bond resulting in a total revenue of 425,424 EUR.

The second part of the dataset includes data regarding the social engagement of an observation group consisting of 2,083 individual users of the online customer network. These users were selected due to their membership in discussion groups dealing with the newly launched financial product under consideration or related topics. For reasons of confidentiality, all personal details have been removed prior to the transfer of the dataset.

2.3 Data analysis and measures

Our paper aims to investigate the relationship between social engagement and customer profitability in the online customer network. In this context, to quantify each individual **user's profitability, we calculated his or her total revenues** regarding the financial product considered for the observation period. According to their customer profitability, we further distinguish three categories in the following: top 1% buyers (21 users), i.e. the 1% users with the highest customer profitability (i.e. with the highest total revenues); buyers (89 users also including the 21 top 1% buyers), i.e. all users with positive customer profitability (i.e.

with positive total revenues); and non-buyers (1,994 users), i.e. all users who have not purchased the financial product under consideration within the observation period.

To quantify each individual user's social engagement in the online customer network, in a first step we determined his or her number of group memberships, his or her number of written group posts, and his or her duration of network membership. In a second step and to enable more in-depth analyses of each user's social engagement in terms of writing and reading group posts within the online customer network's discussion groups, we made use of the fact that the online customer network can be represented as a graph with a set of nodes and a set of directed and weighted edges (ties) linking pairs of nodes (Barrat et al., 2004; Wasserman and Faust, 2009). The respective graph contains 2,083 nodes, representing the users of the online customer network, and 240,900 directed and weighted edges, representing the presence and frequency of social interaction between a pair of users. Thereby, it is important to note that group posts reach all other users who are member of the respective group (i.e. 1:n communication). To analyse the graph representing users' participation in the online customer network's discussion groups and particularly to determine each individual user's respective structural position in the network, we applied Social Network Analysis. Social Network Analysis has been intensively used in IS research to study the structure of networks and the relationships between its members (cf. e.g., Scott, 2013; Kane et al., 2014). In this context, there exist several measures to quantify the centrality of a node and to identify important nodes within a network (Bonacich, 1987; Wasserman and Faust, 2009). The most common centrality measures are closeness centrality, betweenness centrality, degree centrality (Freeman, 1979), and eigenvector centrality (Bonacich, 1972). Closeness centrality can be regarded as a measure of how long it will take information to spread from one user to the other users within the online customer network. This means, users with high closeness centrality can spread information more quickly (Newman, 2005). Betweenness centrality indicates the number of shortest paths from all nodes to all others that pass through a certain node. Hence, users on many shortest paths between other users have higher betweenness centrality and therefore higher influence on the flow of information (Brandes, 2001). Degree centrality is defined as the number of ties a node has. In a directed network such as the examined online customer network of the direct banking institution degree centrality is divided into two separated measures. In-degree centrality indicates the number of edges directed to a node and can be interpreted as the popularity of the user while out-degree centrality describes the node's number of edges directed to other nodes and indicates the user's gregariousness (Opsahl et al., 2010). Eigenvector centrality assigns relative scores to all nodes in the network on basis of their connection to other high scoring nodes. A user in the online customer network with high eigenvector centrality is therefore more important than a user with a low value (Bonacich, 1972).

For our analyses, we used the `igraph`² package for R to calculate closeness centrality, betweenness centrality, eigenvector centrality, and in- and out-degree centrality for each node of the online customer network. In order to interpret the results, the users were ranked depending on their centrality scores for each measure and categorized into four social engagement categories of equal size S25, S50, S75, and “Rest” using the respective quartiles. Hence, for example segments S25 and “Rest” refer to the 25% of all users showing the highest and the lowest centrality scores, respectively.

3 Findings

3.1 Relationship between social engagement and customer profitability in the online customer network

To test if buyers (89 users) have significant higher social engagement compared with non-buyers (1,994 users), we perform a left-tailed two-sample t-test for unequal sample sizes and unequal variances for the social engagement measures number of group memberships, number of written group posts, and duration of network membership as well as for closeness centrality, betweenness centrality, eigenvector centrality, and in- and out-degree centrality (cf. Table 1).

Measures	Buyers (mean)	Non-buyers (mean)	t-stat
Number of Group Memberships	3.40	2.00	-3.43**
Number of Written Group Posts	2.31	2.05	-0.24
Duration of Network Membership [days]	554.78	481.94	-1.29*
Closeness Centrality [%]	19.25	18.93	-0.52
Betweenness Centrality [%]	0.03	0.02	-0.90
Eigenvector Centrality [%]	6.31	10.25	1.56
In-degree Centrality [%]	1.60	2.30	1.36
Out-degree Centrality [%]	0.03	0.05	0.80

* p<0.1, ** p<0.01

Table 1. Results of the left-tailed two-sample t-test for unequal sample sizes and unequal variances for buyers and non-buyers regarding social engagement measures.

The results in Table 1 reveal a significant higher *number of group memberships* ($t\text{-stat} = -3.43125$, $p\text{-value} = 0.00031$) among *buyers* compared with *non-buyers*. Likewise, *buyers* have a significant longer *duration of network membership* ($t\text{-stat} = -1.29264$, $p\text{-value} = 0.09814$) than *non-buyers*. However, the *number of written group posts* of *buyers*

² <http://igraph.org/r/>

is not significantly higher compared with *non-buyers*. Surprisingly, with regard to the centrality measures we do not observe significant higher social engagement values for *buyers* compared with *non-buyers*. On the contrary, when testing vice versa if *non-buyers* have significant higher social engagement compared with *buyers* (i.e. right-tailed two-sample t-test), the centrality measures *eigenvector centrality* ($t\text{-stat} = 1.56089$, $p\text{-value} = 0.05935$) and *in-degree centrality* ($t\text{-stat} = 1.36130$, $p\text{-value} = 0.08678$) are significant ($p > 0.1$). Actually, these results do not support either existing findings in research about social engagement of users and their economic value in online customer networks or best current practices.

4.2 Results of the online customer network analysis

To get deeper insights regarding the interplay between social engagement and customer profitability in the online customer network, on the one hand we used the three categories distinguishing the users according to their customer profitability, i.e. top 1% buyers, buyers, and non-buyers. On the other hand, we differentiated the four quartile-based categories distinguishing the users according to their social engagement measures, i.e. S25, S50, S75 and "Rest". For each customer profitability category (top 1% buyers, buyers, and non-buyers) we calculated the percentage of the respective users belonging to the different quartile-based social engagement categories (S25, S50, S75 and "Rest"). Thereby, we first focus on the social engagement measures number of group memberships, number of written group posts, and duration of network membership (cf. Table 2).

Customer Profitability	Number of Group Memberships				Number of Written Group Posts				Duration of Network Membership [days]			
	S ₂₅	S ₅₀	S ₇₅	Rest	S ₂₅	S ₅₀	S ₇₅	Rest	S ₂₅	S ₅₀	S ₇₅	Rest
Top 1% Buyers	38%	29%	24%	9%	24%	14%	29%	33%	43%	43%	0%	14%
Buyers	40%	28%	24%	8%	22%	22%	26%	29%	30%	26%	16%	28%
Non-buyers	24%	25%	25%	26%	25%	25%	25%	25%	25%	25%	25%	25%

Table 2. Users classified according to their customer profitability and their overlap with the social engagement categories for number of group memberships, number of written group posts, and duration of network membership.

Table 2 highlights that buyers have a higher number of group memberships than non-buyers. 68% of the buyers are among the first two social engagement categories S25 (40%) and S50 (28%) compared with only 49% of the non-buyers. Only 8% of the buyers belong to the category "Rest" containing the users with the fewest group memberships. For the measure duration of network membership also comparatively more buyers than non-buyers can be found in the top category S25: 30% of all buyers and even 43% of the top 1% buyers are among the top 25% users with respect to the duration of network membership. In contrast, only 25% of the non-buyers belong to this top category. On the contrary, the

results for the number of written group posts differ considerably. For this social engagement measure non-buyers are characterized by higher overlaps with the respective top social engagement categories S25 and S50. Indeed, only 38% of the top 1% buyers belong to the first two categories while this is the case for 50% of the non-buyers.

In a second step, we focus on users' individual structural positions in the online customer network represented by the centrality scores for closeness centrality, betweenness centrality, eigenvector centrality, as well as in- and out-degree centrality (cf. Table 3 and Table 4).

Customer Profitability	Closeness Centrality				Betweenness Centrality				Eigenvector Centrality			
	S ₂₅	S ₅₀	S ₇₅	Rest	S ₂₅	S ₅₀	S ₇₅	Rest	S ₂₅	S ₅₀	S ₇₅	Rest
Top 1% Buyers	14%	29%	43%	14%	24%	10%	48%	19%	29%	43%	19%	10%
Buyers	11%	31%	34%	24%	34%	9%	35%	22%	26%	36%	25%	13%
Non-buyers	26%	25%	25%	25%	25%	26%	25%	25%	25%	24%	25%	26%

Table 3. Users classified according to their customer profitability and their overlap with the social engagement categories for closeness centrality, betweenness centrality, and eigenvector centrality.

Customer Profitability	In-degree Centrality				Out-degree Centrality			
	S ₂₅	S ₅₀	S ₇₅	Rest	S ₂₅	S ₅₀	S ₇₅	Rest
Top 1% Buyers	29%	43%	19%	10%	14%	19%	38%	29%
Buyers	27%	35%	27%	11%	11%	31%	30%	27%
Non-buyers	25%	25%	25%	26%	26%	25%	25%	25%

Table 4. Users classified according to their customer profitability and their overlap with the social engagement categories for in- and out-degree centrality.

Our prior analyses and statistical tests based on these measures do not show significant higher social engagement of buyers compared with non-buyers. Even though, the descriptive findings in Table 3 und Table 4 illustrate interesting differences in the relative allocation with respect to the social engagement categories (S25, S50, S75 and "Rest") for top 1% buyers, buyers, and non-buyers, respectively.

A closer look at the top category S25 for closeness centrality reveals that buyers are much less often characterized by very high centrality scores compared with non-buyers. Indeed, only 11% of the buyers and 14% of the top 1% buyers belong to the top category while this is the case for 26% of the non-buyers. Closeness centrality is based on a user's shortest paths to all other users in the online customer network. The normalized version used in this research inverts the sum of the lengths of the shortest paths to all other users so that larger values represent higher centrality (cf. Freeman, 1979). Hence, it can be concluded that buyers do not receive information more quickly within the online customer network than non-

buyers. Focusing on betweenness centrality only 34% of the top 1% buyers and 43% of the buyers, but 51% of the non-buyers belong to the first two social engagement categories (S25 and S50). According to Freeman (1979), users characterized by a high betweenness centrality are acting as gatekeepers, hence important distributors of information, between disparate regions of the online customer network. For out-degree centrality buyers are less often represented in the first quartile S25 (11%) compared with non-buyers (26%) as well. In general, the centrality measure out-degree centrality indicates a user's ties to other users in the network (cf. Freeman, 1979). For our weighted graph representing users' participation in the online customer network, it more concretely reflects the total number of interactions between a pair of users initiated by the respective user under consideration.

In contrast, for eigenvector centrality and in-degree centrality a broad majority of the (highly) profitable customers are among the first two social engagement categories S25 and S50. Indeed, for eigenvector centrality 72% of the top 1% buyers and 62% of the buyers belong to these categories, but only 49% of the non-buyers. For in-degree centrality, we observe very similar results: 72% of the top 1% buyers and 62% of the buyers belong to the two top categories, but only 50% of the non-buyers. Related to out-degree centrality, in-degree centrality represents the total number of a user's interactions initiated by one of his or her neighbours in the network (cf. Freeman, 1979). Eigenvector centrality is a recursive version of the degree centrality measure. Here, a user is regarded as central when he or she interacts with other central users (cf. Bonacich, 1972).

5 Discussion, Limitations, and Future Research

5.1 Discussion and implications for theory and practice

This study has investigated in-depth the relationship between customers' social engagement and customer profitability in online customer networks using a dataset of a German direct banking institution. The dataset contains unique information regarding the customers' social engagement and their financial data. Our study contributes to theory and practice in various ways.

First of all, we do not generally observe significant higher social engagement for "buyers" compared with "non-buyers" in the investigated online customer network. This insight does not support existing statements in literature where a positive relationship between customer profitability and social engagement is predominantly argued (cf. e.g., Manchanda et al., 2015; Kim and Ko, 2012; Goh et al., 2013; Rishika et al., 2013; Zhu et al., 2012). In contrast to our findings Manchanda et al. (2015), for example, found a 19% increase in revenue triggered by online customer network membership and social engagement based on a long term investigation of economic effects of membership and participation in an online customer network. However, although rare, not all previous research observed mere

positive effects of social engagement in online customer networks on customer profitability. Algesheimer et al. (2010), for instance, recognized also negative effects on the bidding and selling behaviour, for example a decline in the amount of money spent per month, due to **customers' social engagement in the online customer network of eBay Germany**. With respect to practice, our findings do not support some prevalent assumptions about the benefits of online customer networks. As a current practice, many companies generally encourage and accelerate a strong participation of users in the company's online customer network. With regard to the examined banking institution for example, users with high level of social engagement are financially rewarded regardless their customer profitability. However, the mere and undifferentiated encouraging of users' social engagement in online customer networks does not seem to be a sufficient practice in view of our results. As a practical implication companies have instead to critically reflect on how to manage online customer networks regarding economic benefits in general and how to manage users' social engagement in particular.

Second, further analysing the characterization of profitable and non-profitable customers (i.e. top 1% buyers, buyers, and non-buyers) with respect to their social engagement in the online customer network, we were able to derive three insights: on the one hand, we found that buyers have a higher number of group memberships and duration of network membership than non-buyers. On the other hand, for the measures number of written group posts, closeness centrality, betweenness centrality, eigenvector centrality and in- and out-degree centrality, we found no significant higher social engagement of buyers compared with non-buyers. A high value for closeness centrality can indicate the possibility to quickly spread information between users in the online customer network (Newman, 2005) while **a high value for betweenness centrality can represent a user's high influence on the flow of information** (Brandes, 2001). Based on our results it may thus be concluded that buyers do not seem to be able to spread information more quickly (indicated by closeness centrality) and also do not significantly more often control the flow of information (indicated by betweenness centrality) than non-buyers. In addition, referring to in- and out-degree centrality, it turns out that buyers have no significant higher probability to interact with other users compared with non-buyers (Opsahl et al., 2010). Buyers have therefore neither a higher popularity (indicated by out-degree centrality) nor are they more gregariousness (indicated by in-degree centrality) than non-buyers. Further, the analysis of the centrality measures reveals even surprising contrary findings. For two centrality measures (in-degree centrality and eigenvector centrality) that describe users' individual structural positions in the online customer network, we observed higher social engagement of non-buyers compared with buyers.

According to the findings and as the basis for further practical applications in the context of the present online customer network of the direct banking institution, we can characterize buyers as generally mature members (duration of network membership) of the online **customer network with a high curiosity about the online customer network's variety of discussion groups** (number of group memberships). However, buyers are not characterized by a significant higher number of written group posts compared with non-buyers. Indeed, this social engagement measure indicates that buyers do not participate more in discussion groups compared with non-buyers even though they are members in more groups and have on average a longer lasting online customer network membership. Our further analyses with centrality measures commonly used in IS research (e.g., Kane et al., 2014) support this observation.

5.2 Limitations and future research directions

Although our research provides first insights about the relationship between customer profitability and social engagement in online customer networks, there are several limitations which can serve as starting points for future research.

First, we only considered the online customer network of one single company which provided us with the relevant data needed to conduct our research. Nevertheless, the online customer network of the direct banking institution is among the most innovative online customer networks for financial products and financial services in Germany. Furthermore, it offers typical functionalities for socialising and information sharing (i.e. maintaining a personal profile, establishing of friend ties, and participating in discussion groups) which are regarded as elementary for online customer networks (cf. e.g., Muniz and O'Guinn, 2001; McAlexander et al., 2002). **Combined with the users' ability to conduct financial transactions via the associated direct banking platform, the online customer network provides an ideal setting to investigate the relationship between customer profitability and users' social engagement.** Therefore, we assume that the results obtained therefrom also hold for other companies. Nevertheless, to increase the generalizability of our results for heterogeneous online customer networks, future research should investigate further online customer networks.

Second, we focused on one single financial product of the direct banking institution. Naturally, including revenue figures generated from a wider range of financial products and financial services would mean to investigate more users. We believe that the newly launched financial product is suit-able as a starting point for our research due to the lively exchange of ideas in the discussion groups about the financial product. In order to investigate differences between various product groups regarding the relationship between **customer profitability and users' social engagement, it is necessary for future research to include a wider range of financial products and financial services.**

Third, the evaluation of social engagement in the online customer network focuses on memberships and posts in discussion groups. Obviously, discussion groups do not completely reflect the social engagement of users in the online customer network. However, the participation of users in the various discussion groups is by far the most frequently used feature of the online customer network. All of the 2,083 users under observation are members of one or more of the analysed discussion groups and more than 53% of the users are author of at least one group post. Nevertheless, in order to capture the whole range of **users' social engagement it is necessary for future research to extend** the investigation also to less-used functionalities like the establishing of friendship ties or private messages.

Fourth, we did not conduct an in-depth content analysis how the valence of the written group posts affects users of the online customer network. Therefore, we did not consider, for example potential negative group posts about the financial product under observation (cf. Kumar et al., 2010), and did not reject off-topic group posts, for example about other financial products or financial services of the banking institution. However, the discussion groups for our research were selected according to their relevance for the newly launched financial product. We assume therefore that a high number of the respective group posts in the observation period refer to the financial product under observation. Nevertheless, future research should include a content analysis of group posts in order to better understand the content part of the online customer network.

Finally, not all aspects of the social connections and communication were considered in our social network analysis. Nonetheless, we applied the most common centrality measures and **were able to investigate users' centrality in the online customer network** (e.g., Kane et al., 2014). For future research, we suggest a more detailed analysis of the structural characteristics of buyers (e.g., an analysis of interrelationships between top classified users). Also further characteristics such as demographic information (e.g., sex, age, and place of living) could be integrated in order to get a more comprehensive picture about the relationship between customer profitability and **users' social engagement** in online customer networks.

6 Conclusion

This research investigates the relationship between customer profitability and **users' social engagement** in online customer networks. A dedicated social engagement of customers in **a company's online customer network is widely seen as strategically important in order to** establish a competitive advantage and as a foundation for future business success (Brodie et al., 2013). Therefore, it is not surprising that companies have a strong interest in establishing and developing online customer networks in order to take advantage of these benefits (Agarwal et al., 2008; Baldus et al., 2015). However, to this date, little is known in **depth about the relationship between customers' social engagement and customer profitability** in online customer networks. Thus, the aim of our paper is to provide novel insights

about the relationship between customers' social engagement and customer profitability in online customer networks using a dataset of a German direct banking institution's online customer network. The dataset contains unique information regarding the customers' social engagement and their financial data. To quantify each individual user's profitability, we calculated his or her total revenues regarding the financial product considered for the observation period. According to their customer profitability, we further distinguished customers into the three categories top 1% buyers, buyers, and non-buyers. To quantify each individual user's social engagement in the online customer network, we determined his or her number of group memberships, his or her number of written group posts, his or her duration of network membership as well as common centrality measures such as closeness centrality, betweenness centrality, degree centrality (Freeman, 1979), and eigenvector centrality (Bonacich, 1972). Based on Social Network Analysis (cf. e.g., Scott, 2013), we derive interesting findings that do not support either existing statements in literature or best current practices: First, we found that in the context of the investigated direct banking institution's online customer network "buyers" are not generally characterized by significant higher social engagement compared with "non-buyers". This insight is not in line with existing statements in literature where a positive relationship between customer profitability and social engagement is predominantly argued (cf. e.g., Manchanda et al., 2015; Kim and Ko, 2012; Goh et al., 2013; Rishika et al., 2013; Zhu et al., 2012).

Second, when analysing the characterization of top 1% buyers, buyers, and non-buyers with respect to their social engagement in the online customer network, we found that buyers have a higher number of group memberships and duration of network membership than non-buyers. In contrast to existing statements in literature, the analysis of the residual social engagement measures, especially the centrality measures commonly used for social network analysis in IS such as closeness centrality, betweenness centrality, eigenvector centrality and in- and out-degree centrality (cf. Bonacich, 1972; Freeman, 1979), reveal that there is no significant higher social engagement of buyers compared with non-buyers. Finally, for the centrality measures in-degree centrality and eigenvector centrality the analyses even show that non-buyers have a significant higher social engagement than buyers.

Overall, the results are unexpected. Following our results, companies have to critically reflect on how to manage online customer networks regarding economic benefits in general and how to manage users' social engagement in particular. With our results, we hope to contribute to a better understanding of the relationship between customer profitability and social engagement in online customer networks. We hope that our present findings will stimulate further discussion and research on that interesting topic and support practitioners to better understand and use online customer networks.

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2.2 The Impact of Social Engagement on Customer Profitability – Insights from a Direct Banking Institution’s Online Customer Network

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Abstract

The digital transformation leads to an enormous change in the customer-firm relationship. Recently launched firm-sponsored online customer networks enable customers to actively interact with the company and other customers in form of social engagement activities like asking and answering questions or receiving feedback. Despite the increasing importance of online customer networks, existing literature still lacks an in-depth understanding of the impact of social engagement on customer profitability based on real-world data regarding both customers’ social engagement activities and customers’ profitability. Our paper therefore aims at providing insights about the relationship between different forms of customers’ social engagement and customers’ profitability based on an extensive dataset of a German direct banking institution’s online customer network. We found, for example, that – in contrast to posting answers – raising questions in the online customer network is associated with significantly higher profitability of the respective customers. Our study leads to interesting results exceeding existing research and helping practitioners to manage online customer networks more effectively and to focus on and foster particularly promising forms of customers’ social engagement.

Keywords: Online Customer Network, Social Engagement, Customer Profitability, Direct Banking Institution.

1 Introduction

The enormous growth of social media in recent years tremendously altered the relationship between customers and firms (Internet Live Stats, 2016; eMarketer, 2016) and has not only **turned customers' small-scale** offline friendship networks into far-reaching online social relationship networks, but also changed the spread of information and influence among customers dramatically (e.g., Kaplan and Haenlein, 2010). In addition to their social media presence on platforms like Facebook or Twitter, companies seek to establish firm-sponsored online customer networks in order to create an ongoing beneficial relationship towards current and potential customers (Porter and Donthu, 2008). Online customer networks are defined as specialised, 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 (Muniz and O'Guinn, 2001; McAlexander et al., 2002). An example is the online customer network of *Oracle*¹ where millions of customers are **connected worldwide to share experiences about the company's products, ask and answer questions, and help each other with specific problems associated with the company's products and services**. The Oracle community, as one among many examples for an online customer network (e.g., Hong, 2015), displays the dramatic change **of customers' role from traditional passive consumers towards creators and publishers of** information, opinions, and emotions about products and services (Di Gangi et al., 2010; Roberts and Dinger, 2016). Due to the social engagement of customers in online customer networks, the influence of customers on other customers as well as on the company itself has increased (van Doorn et al., 2010; Brodie et al., 2011; Sashi, 2012).

Recent studies indicate that **customers' social engagement in an online customer network** is an opportunity to gain competitive advantage through increased customer loyalty which in turn may improve sales and enhance profitability (Martins and Patrício, 2013; IDG Enterprise, 2016; Binder and Hanssens, 2015; Kumar et al., 2007). A study by *Bain & Company*, for instance, observed a 20% to 40% growth in purchase expenditures attributable to **customers' social engagement on companies' online social media platforms** (Barry et al., 2011). Customers engaged in online customer networks are therefore seen as valuable generators of content, considerable co-creators of customer value, and influencing recommenders of products and services towards other customers (Jaakkola and Alexander, 2014; Hajli, 2014).

Against this background, researchers started to investigate the impact of a customer's social engagement in online customer networks on his/her specific economic characteristics such as purchase intention, buying and selling behaviour, financial risk-seeking tendencies, and customer profitability (Algesheimer et al., 2005; Algesheimer et al., 2010; Zhu et al., 2012; Goh et al., 2013; Manchanda et al., 2015; Klier et al., 2016). Due to limitations of existing

¹ <http://community.oracle.com>

research it is, however, still rather unclear if social engagement is indeed associated with higher customer profitability, whether different forms of social engagement play different roles, and how strong the potential impact on customer profitability really is. Actually, there is a lack of in-depth knowledge about the relationship between social engagement and customer profitability. We aim at broadening existing knowledge regarding the influencing factors of successful online customer networks by analysing different forms of customers' social engagement in relationship to customer profitability by using a unique dataset of a **German direct banking institution. The dataset contains information about customers' social engagement in the firm-sponsored online customer network, demographic factors like age and place of residence, as well as individual customers' financial transaction data.**

The remainder of this paper is organized as follows: Section 2 provides an overview about the related literature. In Section 3, the case setting and the dataset are described. Section 4 explains our research model. In Section 5, we present the results of our analysis which are discussed in detail in Section 6. Finally, in Section 7 we conclude our paper with a brief summary of the findings.

2 Theoretical Background

2.1 Research on online customer networks and social engagement

In recent years, the concept of social engagement attracted much attention among practitioners and researchers alike (Kumar et al., 2010; Brodie et al., 2011; Vivek et al., 2012; Dessart et al., 2016). Social engagement in general has been researched in several disciplines such as education, psychology, and management (Erat et al., 2006; Vivek et al., 2014). Triggered by the enormous growth of social media, one particular focus is on **customers' social engagement in online customer networks (e.g., Erat et al., 2006; Dessart et al., 2015)**. Online customer networks are specialised non-geographically bound firm-sponsored online communities which focus on company-related products, services, or topics in order to enhance the communication and information exchange between company and customers and among customers (Muniz and O'Guinn, 2001; McAlexander et al., 2002). Companies therefore started to establish online customer networks in order to be able to interact more intensively with their customers, to maintain social relations marked by mutuality and social bonds, and to allow customers to interact with each other in a variety of ways in comparison to the previous somewhat constricted possibilities in the pre-internet era (Muniz and O'Guinn, 2001; McAlexander et al., 2002; Dholakia et al., 2004; Wiertz and Ruyter, 2007; Brodie et al., 2011; Gummerus et al., 2012). Instead of one-directional communication between company and customers, for example in form of a television commercial, multiple forms of dialogues are nowadays possible, not only between customers and **company but also between customers among themselves (Dholakia and Firat, 2006; Gummerus et al., 2012; Sashi, 2012)**. Matzler et al. (2011) summarized three important

factors of online customer networks which help companies to strengthen their relationship towards their customers: 1) online customer networks are a valuable source of information about the market and the corresponding customers (e.g., Füller et al., 2008), 2) online customer networks form a rallying point for customers who are highly engaged with the product or company and are therefore a source for product development and co-creation (e.g., Bagozzi and Dholakia, 2002), and 3) online customer networks are an ideal basis for building up customer-to-company and customer-to-customer relationships and creating strong brand advocates (Algesheimer et al., 2005; Bagozzi and Dholakia, 2006; Zhang et al., 2015). Online customer networks are in general characterized as enabler of social presence, hence the degree of acoustic, visual, and physical contact that can be achieved through communication between its members (Kaplan and Haenlein, 2010). Through their focus on information sharing, they are further suited to avoid uncertainty and reduce ambiguity (Kaplan and Haenlein, 2010; Gummerus et al., 2012). Finally, online customer networks support the **users' desire of self-presentation and self-disclosure** (e.g., Kaplan and Haenlein, 2010). Summarized, companies, on the one hand, aim to engage with loyal and informative customers, enhance customer relationships, and increase sales (e.g., Algesheimer et al., 2005). Customers, on the other hand, focus on personal benefits when performing social engagement activities with other customers online like acquiring information about products and services or experience social respect, hence the feeling to be useful and needed as a community member (Schau et al., 2009; Nambisan and Baron, 2010; Gummerus et al., 2012).

Social engagement, as an elementary "*concept [...] to capture customers' total set of behavioural activities*" (Gummerus et al., 2012, p. 857), describes customers' online customer network behaviour in form of active participation like asking and answering forum questions and giving and receiving feedback, for example in form of likes (Gummerus et al., 2012; Stone and Woodcock, 2013). To understand the nature of customers' social engagement, van Doorn et al. (2010) proposed a model which comprises five motivational drivers of customers' social engagement behaviours towards a company: **valence, form and modality, scope, nature of its impact, and goals**. Customers' social engagement therefore can 1) have a different polarity (e.g., positive or negative word-of-mouth), 2) be expressed in various forms depending on the available resources (e.g., time vs. money) and results in different types of outcome (e.g., service improvement), 3) vary in scope and momentary (e.g., local vs. global scope), 4) be distinguished according its form of impact (immediacy, intensity, breadth, or longevity), and 5) be based on different purposes by the customers (e.g., regarding direction, wilful intention by the customer, or consistency between customer and company goals) (van Doorn et al., 2010; Gummerus et al., 2012). Nature and extent of social engagement depend highly on the individual users and their personality (Ross et al., 2009; Realo et al., 2011), internet usage patterns (Correa et al., 2010; Brandtzæg et al., 2011), and demographic factors like age or place of residence (e.g.,

Zywica and Danowski, 2008). With respect to customers' intentions, Wirtz et al. (2013) identified company-related, social, and functional drivers that motivate and affect customers' social engagement. *Brand identification* aims at the associations (functional, emotional, and reputational) a customer makes out of his/her identification with a certain product or company (Hughes and Ahearne, 2010; Wirtz et al., 2013). *Social benefits* describes a multitude of benefits to the users of an online customer network, such as receiving assistance from others (Dholakia et al., 2009) or maintaining and strengthening the social identity as a member of a social group (Hughes and Ahearne, 2010; Gummerus et al., 2012). *Functional benefits* arise from uncertainty reduction in purchase decisions (Weiss et al., 2008; Adjei et al., 2010), high quality, broad-based, and up-to-date information about a product or company (Porter and Donthu, 2008; Dholakia et al., 2009), and other monetary and normative incentives, such as price promotions and loyalty programs to encourage long term social engagement (e.g., Garnefeld et al., 2012). These benefits in turn are considered to enhance the willingness and amount of customers' social engagement in online customer networks (e.g., Wirtz et al., 2013). Overall, customers' social engagement is regarded as the key element of online customer networks and describes underlying behavioural activities like discussions, relationship building, commenting, liking, knowledge acquisition, and opinion forming, hence the sum of all human communication and interaction through online customer networks (van Doorn et al., 2010; Gummerus et al., 2012; Brodie et al., 2013).

2.2 Research on customer profitability in online customer networks

Existing research about social engagement in online customer networks focuses merely on non-monetary aspects like the impact of online customer networks on brand awareness and image (e.g., Zhang et al., 2015) or the vast research area of customer value co-creation (e.g., Romero and Molina, 2011). Instead of focusing on customer profitability, research identified the importance of social engagement on customer loyalty (e.g., Dwivedi, 2015) and customer behaviour. However, so far there exists little research on the relationship between social engagement and monetary aspects.

As one of the first, Algesheimer et al. (2005) developed a conceptual framework focusing on customers' intentions in the context of the online customer network of a European car club. According to their study, customers' online behaviour induces corresponding social engagement activities which in turn may positively affect customer profitability. The authors, however, raise the question for future research whether all social engagement activities have a likewise positive impact. Subsequent research based on data from the online auction platform *ebay* about online customer network membership revealed mixed effects on customers' buying and selling behaviours (Algesheimer et al., 2010). The authors observed, against their expectation, no general positive influence of online customer network

participation neither on the revenue nor on the number of bids placed. Partly, even a negative impact on the number of listings and the money spent was noted. By analysing customers' lending behaviour, Singh et al. (2015) investigated for the online customer network of the peer-to-peer microcredit provider *kiva.org* a positive impact of mere group membership on both the number of loans granted and the amount of loaned money. Kim and Ko (2012) examined customers' social media activities on luxury fashion brand fan pages to identify effects on purchase intentions and customer equity. By manually analysing content data of social networks, the authors noticed that enhanced social engagement can indeed have a positive effect on customer equity drivers and purchase intentions. Likewise, Goh et al. (2013) laid their focus on the economic value of a company's social media fan page. By analysing individual generated user content, the authors found a positive increase in purchase expenditures depending on stronger social engagement. Rishika et al. (2013) quantified customers' participation on a company's social media platform to investigate the impact on customer profitability. They observed a positive relationship between customers' social engagement, however limited to the number of page visits, and customer profitability. The study conducted by Manchanda et al. (2015) investigated the hypothesis that customers engaged in an online customer network also have an increased economic activity. Based on a dataset of an entertainment retailer with a recently launched online customer network, the results revealed significantly higher expenditures for customers participating in the retailer's online customer network. Controversially to most of previous research, Klier et al. (2016) did not observe higher profitability for customers with higher social engagement for the online customer network of a direct banking institution. Social engagement was measured for example in form of the number of group membership or the duration of network membership. The analysis, however, was conducted on a limited dataset for customers' social engagement activities and restricted to a very specific bank capital bond with correspondingly low turnover.

2.3 Research gap and intended contribution

Due to the influence on customers' purchase decisions, it is important to investigate the relationship between social engagement and profitability in order to enable a more effective management of online customer networks. Beside the general research about social engagement in the context of social media (e.g., Dessart et al., 2015; Kumar et al., 2016), research about customers' social engagement on a company-level and its impact on economic factors is still underdeveloped (e.g., Beckers et al., 2016). On the one hand, customers' social engagement is mostly investigated with focus on a single social engagement activity. On the other hand, studies are not focusing on customer profitability itself (Algesheimer et al., 2010; Zhu et al., 2012; Singh et al., 2015). Moreover, most existing studies about social engagement in online customer networks lack an empirical basis and are "predominantly exploratory in nature" (Hollebeek et al., 2014, p. 149). Other studies with a

more empirical focus are not able to establish a direct link between customers' social engagement data and economic behaviour data (e.g., Algesheimer et al., 2005), are based merely on limited survey data (e.g., Kim and Ko, 2012), or were only able to manually link basic social media behaviour data with financial transaction data (Goh et al., 2013; Rishika et al., 2013). Among existing literature, the studies by Manchanda et al. (2015) and Klier et al. (2016) can be seen as complementary to our research. Manchanda et al. (2015) provided insights into the relationship between online customer network membership and customers' financial behaviour. However, the study lacks a clear distinction between different forms of social engagement, focused merely on a small range of purchased goods, and considered loyalty card holders only. Klier et al. (2016) analysed social engagement data for a limited set of customers and distinguished them into buyers and non-buyers without observing significantly higher social engagement for the buyers. The dataset was, however, limited to only two different types of social engagement. In addition, the small number of customers actually buying the specific product under consideration restricts the generalizability of the study's findings.

Based on existing literature, our study aims at extending existing research on the relationship between social engagement and customer profitability in online customer networks. **Thereby, unlike previous research, we are able to investigate different forms of customers' social engagement activities in combination with customer profitability in form of revenues generated by credit card for more than 100,000 members of the online customer network of a German direct banking institution.** We are therefore neither forced to try to manually link social engagement data with corresponding financial data for a very limited set of customers, nor do we have to estimate respective customers' revenues using more or less restrictive assumptions. Our paper contributes to research by providing novel in-depth findings about the relationship between different forms of social engagement like answers and questions including respective feedback in form of likes and dislikes as well as demographic factors like age and place of residence and customer profitability in the context of online customer networks on basis of an extensive and comprehensive dataset on both social engagement and customer profitability. We are therefore – as one of the first – able to give deeper insights into the interplay between social engagement and customer profitability. **We help thereby companies to understand and manage customers' social engagement possibilities in general and the impact of social engagement activities in particular within their online customer networks.**

3 Case Setting and Data

The 2009-founded German direct banking institution offers a wide range of traditional and innovative financial products and services ranging from classical giro accounts to contemporary social lending services. Furthermore, the institution operates one of the most active

financial online customer networks in Germany with more than 310,000 registered members which is consequentially regarded as major competitive advantage against competing financial institutions. The main features of the online customer network are the public forums where customers can discuss about financial topics, give mutual investment tips, evaluate financial products and advisors, and propose new products or services. Basically there are two forum types where customers can ask and answer questions. On the one hand, the group forum which serves as a discussion board where customers typically exchange experiences, opinions, and advice about a wide range of general financial topics like saving, tax reduction, or investment. On the other hand, the money forum where customers share concrete financial investment opportunities like stock trading strategies or investment opportunities, discuss current financial issues with other customers, or propose new financial products and services. Furthermore, posts in the money forum can be rated by each customer in form of likes and dislikes to account for a qualitative content assessment. **Summed up, the main purpose of the online customer network is to foster customers' interaction with the banking institution and between themselves.**

For our research, the direct banking institution provided us with a dataset ranging from 23rd July 2015 to 22nd July 2016 containing information about 112,149 registered customers. Due to reasons of confidentiality, all personal details have been removed or anonymised **prior to the transfer of the dataset. To account both for customers' social engagement activities and customers' financial transactions the dataset consists of three parts.**

The first part refers to the customers' social engagement activities in the online customer network. For each customer, the dataset contains the number of questions and answers contributed to the group forum (*QuestionsGroup*, *AnswersGroup*) and the money forum (*QuestionsMoney*, *AnswersMoney*). Additionally, the money forum specific number of received likes (*LikesMoney*) and dislikes (*DislikesMoney*) are included. Considering customers' social engagement in form of questions (*QuestionsGroup*, *QuestionsMoney*) and answers (*AnswersGroup*, *AnswersMoney*) in discussion forums is consistent with existing literature (e.g., van Doorn et al., 2010). By investigating the online customer network of *ebay*, Algesheimer et al. (2010), for example, observed considerable social engagement activities in the numerous discussion forums. However, the authors lack a distinguishing between different forms of social engagement like answers and questions. Received feedback on social engagement activities in form of likes and dislikes (*LikesMoney*, *DislikesMoney*) reflects the **network's appreciation for the quality of the customer's contributions to the online customer network** (e.g., Stone and Woodcock, 2013). Existing research analysed feedback on social engagement activities and discovered a higher perceived quality due to positive feedback (e.g., Sashi, 2012; Swani et al., 2013; Zhu et al., 2013; Cheng et al., 2014). Negative feedback in contrary is attributable to less written questions and a lower quality of answers

(e.g., Zhu et al., 2013; Cheng et al., 2014). The observed likes and dislikes are therefore able to indicate the quality of customers' social engagement.

The second part of the dataset contains information regarding customer profitability which is generally defined as "the net dollar contribution made by individual customers to an organization" (Mulhern, 1999, p. 26) and treats customers as an asset analogous to other economic units (Wyner, 1996). For our research, we use the sum of all credit card transactions per customer in EUR during the time period under observation (*Revenues*) to represent customer profitability. All customers registered in the online customer network account for a total revenue of 233,922,082.80 EUR. Contrary to existing research, we are therefore indeed able to investigate a broad range of customers' financial transactions and are neither limited to a certain product (e.g., Klier et al., 2016) nor a specific customer segment or retail channel (e.g., Manchanda et al., 2015).

Finally, the third part of the dataset contains basic demographic information about each customer's age in years (*Age*) and place of residence (*Residence*). Customers can be segmented in corresponding age groups and differentiated between rural and urban, whereby the latter is defined as cities with more than 100,000 inhabitants. Existing studies already used age and place of residence as control variables (e.g., Algesheimer et al., 2010; Karjaluoto et al., 2015). A descriptive overview with respect to customers' age groups and place of residence is shown in Table 1. Most customers are in the age group of 30 – 39 years (26.69%), followed by the age group of 40 – 49 years (24.33%). In total, 44.65% of all customers live in an urban area. According to existing research, age is one of the most influential factors regarding internet usage (Duggan and Brenner, 2013; Duggan et al., 2015). Therefore, besides customer profitability (Algesheimer et al., 2010; Zhu et al., 2012; Kumar et al., 2016), social engagement activities in the online customer network may also vary depending on customer's age (Algesheimer et al., 2010; Karjaluoto et al., 2015; Zhang et al., 2015). Additionally, regional aspects may influence customer profitability (Algesheimer et al., 2010; Kumar et al., 2016) as well as customers' social engagement (Zywica and Danowski, 2008; Algesheimer et al., 2010).

Number of Customers	Total	Age Group						Place of Residence	
		< 20	20 – 29	30 – 39	40 – 49	50 – 59	> 60	Rural	Urban
Total (in %)	112,149 (100.00)	719 (0.64)	17,090 (15.24)	29,929 (26.69)	27,287 (24.33)	22,588 (20.14)	14,536 (12.96)	62,069 (55.35)	50,080 (44.65)

Table 1. Descriptive information regarding customers' age and place of residence.

With focus on customers' social engagement and customer profitability, Table 2 presents the descriptive statistics. Regarding the total number of questions and answers, the group forum (34,272 posts) contains far less posts compared to the money forum (261,301 posts).

This indicates a general higher interest of customers to discuss specific financial investment opportunities, current financial issues, or the institution's products. Furthermore, in both forums the number of answers (group forum: 27,634; money forum: 230,268) considerably exceeds the number of questions (group forum: 6,638; money forum: 31,033). This customers' willingness to discuss questions is also reflected in the response frequencies: In the money forum, one question is followed on average by more than seven answers; in the group forum by about four answers. In the group forum, 1,544 users wrote at least one question and 1,498 users posted at least one answer. Furthermore, in the money forum, 5,963 users wrote at least one question and 5,330 users posted at least one answer while 3,781 customers received likes and 3,126 users received dislikes. The relatively high maxima regarding *AnswersGroup* (1,522) and *AnswersMoney* (10,293) in combination with the high standard deviations (group forum: 9.99; money forum: 71.57) indicate the existence of few but very strong committed customers with a high number of social engagement activities. In sum, 8,117 customers were active in at least one forum while 40,280 customers generated revenues during the time period under observation. We observed average customer revenues of 1,996.65 EUR, with a minimum of 0.00 EUR, a maximum of 841,589.19 EUR, and a standard deviation of 7,655.35 EUR in the time period under observation.

	Variable	Total	Min	Max	Mean	Std. Dev.
Social Engagement	<i>QuestionsGroup</i>	6,638	0	391	0.059	2.29
	<i>AnswersGroup</i>	27,634	0	1,522	0.246	9.99
	<i>QuestionsMoney</i>	31,033	0	759	0.277	4.73
	<i>AnswersMoney</i>	230,268	0	10,293	2.053	71.57
	<i>LikesMoney</i>	98,315	0	5,592	0.877	33.43
	<i>DislikesMoney</i>	52,618	0	3,089	0.469	15.58
Profitability	<i>Revenues [EUR]</i>	223,922,082.80	0.00	841,589.19	1,996.65	7,665.35

Table 2. Descriptive information regarding customers' social engagement and profitability.

4 Research Model

Figure 1 depicts the research model to investigate the relationship between customers' social engagement and customer profitability. The demographic factors might additionally influence profitability and are important for monitoring possible disruptive effects and to reduce endogeneity issues. As discussed in Section 2.2, prior research started to analyse the relationship between customers' social engagement and diverse monetary aspects like for example customers' financial-related behaviours, purchase decisions, economic value, or profitability (e.g., Algesheimer et al., 2010; Zhu et al., 2012; Kim and Ko, 2012; Manchanda et al., 2015; Klier et al., 2016). In general, existing literature indicates that customers' social engagement goes along with higher customer profitability (Rishika et al., 2013; Karjaluo

et al., 2015; Manchanda et al., 2015; Kumar et al., 2016). Therefore, based on existing literature, we propose the following hypotheses:

H1: A higher number of group forum questions positively relates to higher revenues.

H2: A higher number of group forum answers positively relates to higher revenues.

H3: A higher number of money forum questions positively relates to higher revenues.

H4: A higher number of money forum answers positively relates to higher revenues.

Besides questions and answers in both forums, our dataset also includes information regarding received feedback on written posts in the money forum in form of likes and dislikes (*LikesMoney* and *DislikesMoney*). Based on existing literature (e.g., Swani et al., 2013; Sweeney et al., 2014), we assume on the one hand that customers, who generate a greater number of high-quality social engagement, indicated through a higher number of received likes in the money forum, also have higher customer profitability. On the other hand, we derive that customers with less qualitative social engagement, indicated in form of a higher number of received dislikes, have lower customer profitability (e.g., Moldovan and Goldenberg, 2004). Therefore, we propose the following hypotheses:

H5: A higher number of received likes on money forum posts positively relates to higher revenues.

H6: A higher number of received dislikes on money forum posts negatively relates to higher revenues.

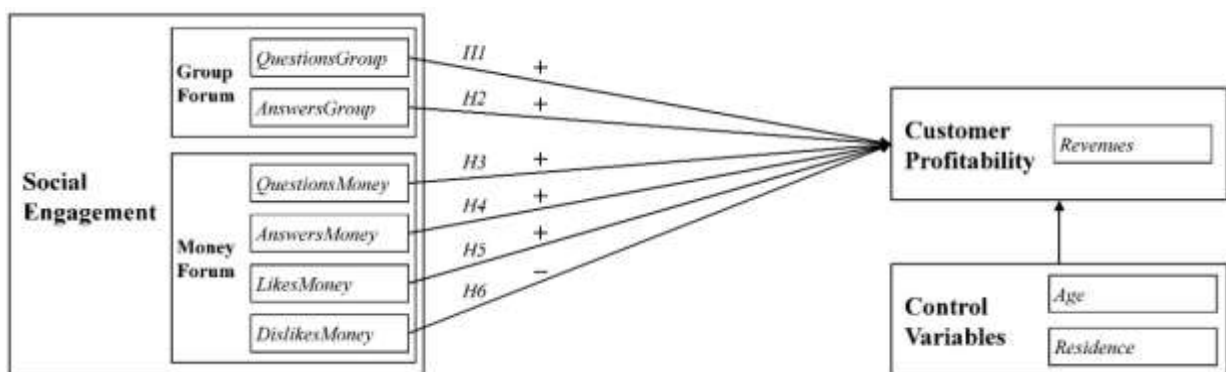


Figure 1. Research model.

To test our hypotheses and to examine the relationship between different forms of social engagement and customer profitability, we adopted a multiple linear regression model with *Revenues* as dependent variable. We used the statistical software package *Stata 13.1* for our analyses. To prevent a bias from potential omitted variables, we controlled the influence of *Age* (in years) and *Residence* (rural (0) vs. urban (1)) as control variables. Our research paper aims in examining the influence of customer's social engagement – represented by

the independent variables *QuestionsGroup*, *AnswersGroup*, *QuestionsMoney*, *AnswersMoney*, *LikesMoney* and *DislikesMoney* – on customer's profitability, represented by the dependent variable *Revenues*. Therefore, we assume the following model:

$$\text{Revenues} = \beta_0 + \beta_1 \text{QuestionsGroup} + \beta_2 \text{AnswersGroup} + \beta_3 \text{QuestionsMoney} + \beta_4 \text{AnswersMoney} + \beta_5 \text{LikesMoney} + \beta_6 \text{DislikesMoney} + \beta_7 \text{Age} + \beta_8 \text{Residence} + \epsilon$$

To address heteroscedasticity, heteroscedasticity-robust standard errors were used in our model (Wooldridge, 2002, p. 57). In general, revenues are explained by the great influence of diverse aspects, like for example customers' income. However, the aim of our study was not to create a prognosis model but to show the effect of customers' social engagement on customer profitability.

5 Findings

5.1 Correlation analysis

Table 3 displays the results of the Spearman rank correlation analysis (Cohen et al., 2003).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) <i>Revenues</i>	1.000								
(2) <i>QuestionsGroup</i>	0.101*	1.000							
(3) <i>AnswersGroup</i>	0.093*	0.716*	1.000						
(4) <i>QuestionsMoney</i>	0.134*	0.259*	0.269*	1.000					
(5) <i>AnswersMoney</i>	0.121*	0.292*	0.329*	0.677*	1.000				
(6) <i>LikesMoney</i>	0.102*	0.279*	0.323*	0.659*	0.727*	1.000			
(7) <i>DislikesMoney</i>	0.095*	0.275*	0.303*	0.649*	0.607*	0.633*	1.000		
(8) <i>Age</i>	0.045*	-0.036*	-0.037*	-0.032*	-0.052*	-0.033*	-0.029*	1.000	
(9) <i>Residence</i>	-0.026*	0.002	0.003	-0.004	-0.001	0.002	0.003	-0.082*	1.000

* p<0.1

Table 3. Spearman rank correlation matrix.

Almost all variables, except the control variable *Residence*, are significantly correlated. A striking fact is in particular the correlations among the independent variables. This indicates (strong) dependencies between the variables representing customers' social engagement. We additionally checked the Variance Inflation Factor (VIF) to test multicollinearity. According to Kennedy (2003), a VIF higher than 10 indicates a problem with multicollinearity. In our study, the VIF values (with a mean of 3.65) do not indicate a harmful collinearity. Considering context and aim of our study on explicitly getting insights with respect to different forms of customers' social engagement, the results can be intuitively explained. For example, the high correlations between questions and answers in both forums (cf. *QuestionsGroup* and *AnswersGroup* with a correlation coefficient of 0.716 and *QuestionsMoney*

and *AnswersMoney* with a correlation coefficient of 0.677) seem naturally consistent because a customer asking many questions and therefore being very active in the online customer network in this respect may indeed also have the tendency to write more answers. The control variables *Age* (correlation coefficient of 0.045) and *Residence* (correlation coefficient of -0.026) indeed show significant correlation coefficients with respect to the independent variable *Revenues*. This highlights the necessity to include *Age* and *Residence* as control variables in our regression model. Furthermore, as Table 3 indicates, while we observe significant negative correlation coefficients for *Age* and the social engagement variables, the correlations between *Residence* and the social engagement variables are not significant.

5.2 Regression results

The regression results provided in Table 4 indicate a mostly positive influence of social engagement on customer profitability. Hypotheses *H1*, *H2*, and *H3* can be confirmed while hypothesis *H4* has to be rejected. A higher number of group forum questions (*H1*) and answers (*H2*) as well as a higher number of questions in the money forum (*H3*) go along with significantly higher customer revenues. Furthermore, we observe a significant but surprisingly negative coefficient for *AnswersMoney* (*H4*: $\beta_4 = -2.27$ EUR, $p = 0.000$) which indicates a striking difference between the two forums. Further, the results of the regression model support *H5* whereas *H6* is not supported. Hypothesis *H5* indicates a significant positive relationship between received likes on money forum posts (*LikesMoney*) with customer profitability (*Revenues*). In contrary, hypothesis *H6*, where a higher number of received negative feedback in the money forum (*DislikesMoney*) is, although negatively related to customer profitability, not statistically significant ($\beta_6 = -3.07$ EUR, $p = 0.113$).

Variables	Coefficient	Robust Std. Err.	P> t	Hypotheses
β_0 (Constant)	1,637.32***	82.34	0.000	
β_1 (<i>QuestionsGroup</i>)	33.47**	15.28	0.029	<i>H1</i> : supported
β_2 (<i>AnswersGroup</i>)	5.71**	2.74	0.037	<i>H2</i> : supported
β_3 (<i>QuestionsMoney</i>)	14.56***	4.29	0.001	<i>H3</i> : supported
β_4 (<i>AnswersMoney</i>)	-2.27***	0.65	0.000	<i>H4</i> : not supported
β_5 (<i>LikesMoney</i>)	3.03**	1.50	0.044	<i>H5</i> : supported
β_6 (<i>DislikesMoney</i>)	-3.07	1.94	0.113	<i>H6</i> : not supported
β_7 (<i>Age</i>)	9.40***	1.59	0.000	
β_8 (<i>Residence</i>)	-122.42***	46.32	0.008	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Results of the regression model.

6 Discussion, Limitations and Future Research

6.1 Discussion of the implications for theory and practice

Our research has investigated the relationship between different forms of social engagement and customer profitability using an extensive dataset of the online customer network of a German direct banking institution. Therefore, our research contributes to theory and practice in various ways.

First, we observed a significant positive influence of most of the social engagement variables on customer profitability (*Revenues*) (cf. Table 4). Questions and answers in the group forum ($\beta_1=+33.47$ EUR, $p=0.029$; $\beta_2=+5.71$, $p=0.037$) as well as questions in the money forum ($\beta_3=+14.56$ EUR, $p=0.001$) indicate higher customer profitability. A noticeable exception is the significant negative influence of answers in the money forum on customer profitability ($\beta_4=-2.27$ EUR, $p=0.000$). A negative relationship between social engagement and profitability is only supported by very few studies (e.g., Algesheimer et al., 2010) and may probably be explained by active but at the same time sceptical members of the online customer network who critically discuss and comment on other customers' questions. However, the significant increase of customer profitability related to customers' social engagement activities observed on a large scale in our study is in line with most of the existing research about the influence of online customer network membership on customers' expenditures, financial risk seeking tendencies, or general purchase behaviours (Kim and Ko, 2012; Zhu et al., 2012; Goh et al., 2013; Rishika et al., 2013; Manchanda et al., 2015). For example, Rishika et al. (2013) observed a 13.5% increase in customer profitability traced back to customers' social media activities on a recently launched company's social media fan page. Beyond that, we were, contrary to existing research, able to directly link social engagement data with revenues and were not limited to manually linked, survey-based, or estimated datasets. We further examined – as one of the first – the influence of different forms of social engagement on customer profitability in more detail and observed a significant positive impact on customer profitability by asking questions in contrary to a less positive or even negative impact on profitability by giving answers. On the one hand, questions in both forums go along with a significantly higher customer profitability ($\beta_1=+33.47$ EUR; $\beta_3=+14.56$ EUR). Answers, on the other hand, go along with a significant but lower increase in profitability in the group forum ($\beta_2=+5.71$ EUR) or even with a significant decrease in customer profitability in the money forum ($\beta_4=-2.27$ EUR). Obviously, a distinction between different types of social engagement is necessary. Regarding practical implications, our findings reveal the impact on profitability by customers' social engagement. Based on our findings, we generally recommend practitioners therefore to focus on encouraging customers to actively participate in the company's online customer network. Since online customer networks are intended to deliver added value for the customers, we further encourage practitioners to

provide the opportunity for customers to ask questions. Indeed, in the investigated online customer network the relevance of questions can be exemplary seen in the observed response frequency with up to seven answers per question. By formulating and replying, customers are animated to actively deal with the topic on hand, presumable with the side effect to steer attention to corresponding products or services of the company. This in turn can have a positive impact on the disposition to buy further products and services. **Customers' social engagement in form of asking and answering product related questions may further help companies to cut down costs for otherwise necessary customer information services, like customer call centres.** With this knowledge in mind, practitioners are additionally able to optimize their online participation reward programs to focus on more promising forms of social engagement and encourage corresponding activities of customers in online customer networks. The institution under investigation of our study recently started a corresponding reward program and is now, based on our research, able to abandon its equally **treatment of customers' social engagement activities to focus on more relevant ones, like for example asking and answering questions in the group forum.** This helps the institution to spend marketing activities aiming at the enhancement of social engagement activities more wisely and targeted. Beside higher profitability, customers with a high social engagement are also regarded **to have a stronger influence on other customers' purchase decisions** compared to customers with low social engagement (Algesheimer and von Wangenheim, 2006; Libai et al., 2013). Instead of generally rewarding customers for their social engagement without distinguishing between different forms of social engagement, companies should therefore in contrary focus on social engagement activities with the most positive influence on customer profitability.

Second, we observed a significant positive relationship between received positive feedback **regarding customer's social engagement (*LikesMoney*)** and his/her profitability (*Revenues*) ($\beta_5=+3.03$ EUR, $p=0.044$). In contrast, we found a, however not significant, negative relationship between received negative feedback (*DislikesMoney*) and profitability (*Revenues*) ($\beta_6=-3.07$ EUR, $p=0.113$) (cf. Table 4). Although there exists little research about the impact **of fellow customers' feedback in form of likes or dislikes on customer profitability in the context of online customer networks,** studies generally investigated the reasons why customers give positive or negative feedback on social media content (e.g., Swani et al., 2013; Zhu et al., 2013; Cheng et al., 2014) and how customers can be encouraged to favourable online behaviour in the context of advertising effectiveness (e.g., Lee and Hong, 2016). In general, customers are interested in informative, entertaining as well as emotional forum posts and are willing to reward the fulfilment of their requirements with approval, for example in form of liking a certain post (Berger and Milkman, 2012; Swani et al., 2013; Lee and Hong, 2016). The opposite applies for uninteresting, unnecessary, or rude forum posts which convey the impression of wasted time and are prone to be punished by the customers

by disliking a post (e.g., Cheng et al., 2014). The observed social engagement variables *LikesMoney* and *DislikesMoney* therefore can give insights about the quality of the content of a specific customer's posts. We advise practitioners to focus on customers who receive many likes, directly encourage their posting behaviour, and reward their high quality contributions in order to higher their customer profitability but also to enhance as a side effect customers' social engagement activities in the online customer network and therefore profitability as a whole. Customers in turn will experience self-assurance through the positive response in form of likes and are thus assumable even more closely tied to the online customer network.

Finally, regardless of the place of residence, customers' age in the online customer network of the German direct banking institution negatively correlates with customers' social engagement activities (cf. Table 3). Only a minority of 16% of all observed customers are younger than 30 years (cf. Table 1). However, our analysis shows that the younger a customer, the higher is his/her social engagement. This indicates that with increasing age the social engagement activity decreases. This age distribution reflects the age distribution of Internet users in general (e.g., comScore, 2014) and social media users in particular (e.g., Duggan and Brenner, 2013; Duggan et al., 2015). Nevertheless, although young customers are not the most wealthy age group (Deutsche Bundesbank, 2016), companies should focus on encouraging social engagement of young customers in order to revive the online customer network with more social engagement and bind promising customers for future revenues (e.g., Larivière and Van den Poel, 2005; Perrin, 2015). Additionally, we observed that a rural place of residence (0) goes along with a significantly higher customer profitability compared to an urban one (1) (cf. Table 4). However, due to the innovative nature of both the online customer network and the online banking institution itself, a higher profitability of customers from the urban region may have been expected (e.g., Eurostat, 2013). We propose, the direct banking institution should on the one hand focus on encouraging customers outside of the big cities to participate more in the online customer network, for instance by linking the pricing for financial products (e.g., free credit card fee) with the individual level of social engagement and on the other hand intensify marketing activities in order to increase the degree of brand awareness among urban customers in general. The online customer network acts as the main differentiator towards rival traditional banking institution. Therefore, a real risk of losing a unique selling proposition exists for the banking institution under investigation when missing the chance to encourage more customers to actively participate in the online customer network in the long run and become thereby strong brand advocates (e.g., Constantinides and Fountain, 2008; Zhang et al., 2015).

6.2 Limitations and future research directions

Although we were able to provide in-depth insights about the relationship between different forms of customers' social engagement and customer profitability, we want to point out limitations of our research and provide possible starting points for future research.

First, since we merely investigated a single online customer network, future research should aim at including online customer networks of other companies, like for example the *SAP Community Network* (go.sap.com/community.html), *Lego Lugnet* (www.lugnet.com), or *My Starbucks Idea* (mystarbucksidea.force.com) (e.g., Hong, 2015). Although we analysed a unique dataset of an online customer network in connection with extensive social engagement and financial transaction data, the generalizability of the observed findings may be limited. Firm-sponsored online customer networks are prone to be monothematic like the financial focus of the investigated online customer network (e.g., Muniz and O'Guinn, 2001). We further were only able to investigate data from one country (Germany) and could therefore not analyse possible country-specific results. Therefore, an extension of topics and data from several countries are additionally desirable in order to get a broader and more comprehensive picture.

Second, due to lack of available data, we could neither consider the content nor the polarity of forum posts and could not perform sentiment and text mining analysis in order to distinguish between positive and negative social engagement (Vinodhini and Chandrasekaran, 2012; Liu, 2012). Even though we were able to investigate different forms of social engagement in the online customer network of the direct banking institution, a deeper analysis of social engagement on basis of content analysis seems preferable, for example to investigate the significant and surprising negative influence of *AnswersMoney* on customer profitability in more detail. As little is known so far in general about the content-related influence of social engagement on customer profitability, we would like to encourage researchers to conduct next steps into this direction.

Third, the observed correlations between the social engagement variables and customer profitability are, although significant, not quite strong (cf. Table 3). This is due to the circumstance that customers' social engagement in online customer networks is only one among many factors influencing customer profitability. Beside social engagement there can be, for example, historical customer behaviour (e.g., existing product ownership, present monetary value, or cross-buying behaviour), intermediary variables (e.g., selling tendency or sales assortment), or general factors like gender, income, or wealth influence customer profitability (e.g., Larivière and Van den Poel, 2005). The contribution of our research paper is first and foremost to provide an in-depth analysis of customer profitability in the context of online customer networks with specific focus on different forms of social engagement.

Since the aim of our research was not to provide an overall forecasting model for profitability, the simplified empirical model seems appropriate for our context and may serve as a sound basis for future works.

Finally, we analysed an extensive dataset about customers' sales, however neglecting thereby the costs when considering customer profitability. Due to the dataset available we were only able to focus on credit card revenues as customer profitability, although there exists of course a broader perspective on customer profitability. In order to get a more **comprehensive view about customers' profitability**, we propose to include more detailed information about sales and costs in future research. Further, regarding the time period under investigation, an expansion of the observed time frame is desirable.

7 Conclusion

In the digital age, social engagement in online customer networks is widely seen as a primary driver of growth in sales and profit (Brodie et al., 2013; Beckers et al., 2016). Companies therefore try to stimulate customers who participate in online customer networks to enhance existing social engagement activities in order to build a sustainable competitive advantage (van Doorn et al., 2010; Brodie et al., 2013; Verhagen et al., 2015). While the positive influence of social engagement on purchase behaviour, value co-creation, or customer loyalty is widely acknowledged in literature (e.g., Williams and Cothrel, 2000; Romero and Molina, 2011; Dwivedi, 2015), there exists little research about the influence of different forms of social engagement on customer profitability. Thus, the aim of our research paper is to provide novel insights into the relationship between different forms of social engagement and customer profitability based on an extensive dataset of the online customer network of a German direct banking institution. The dataset comprises all of the **institution's customers' social engagement activities and revenues generated by credit card**. In order to test our hypotheses regarding the positive influence of social engagement on customer profitability, we applied a multiple linear regression model with *Age* and *Residence* as demographic control variables. Based on our analysis, we observed several interesting findings: First, we found a mostly significant positive influence of social engagement on customer profitability. By in-depth analysing different forms of social engagement, we observed further a significant higher influence of questions compared to answers. Second, by analysing received feedback on written posts in the money forum, we found that positive feedback on money forum posts in form of likes go along with higher customer profitability in contrary to negative feedback in form of dislikes. By investigating different forms of social engagement, we considerable extend existing literature and broaden the knowledge about social engagement in online customer networks. Further, our findings support practitioners in the successful management of online customer networks and increase of future customer profitability by focusing on valuable customers in the online customer network. We hope

that our research stimulates further discussion and research about the relationship between social engagement and customer profitability in online customer networks.

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2.3 The Hidden Moods of Customers - Analysing the Sentiment of Customers' Social Engagement Activities in a firm-sponsored Online Customer Network

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Abstract

This research analyzes the relationship between customer sentiment and revenues based on a dataset from the online customer network of a German direct banking institution. The huge amount of user-generated content through social engagement activities in online customer networks represents a major challenge but also a great opportunity for companies. However, despite its importance, there is a lack of detailed investigation of customers' sentiment in the existing literature. The results of this research indicate a higher share of social engagement activities with a positive sentiment and that the sentiment of an initial activity is also predominantly observed in the subsequent reactions to it. Furthermore, customers with an overall negative sentiment have surprisingly higher revenues compared to customers with an overall neutral or positive sentiment. The study helps companies to manage their online customer networks more effectively and to understand the impact of customers' hidden moods on revenues.

Keywords: *Online Customer Network, Sentiment Analysis, Social Engagement, Direct Banking Institution*

1 Introduction

The trend towards online social networks has continued unabated in recent years and is expected to grow undiminished in future [1]. Billions of users are engaged on a daily basis in social media services such as *Facebook* or *YouTube* [2, 3]. Among other things, they have gained the opportunity to exchange information about companies and their products and services worldwide with an increasing speed [4–7]. **From a company's perspective, these changed conditions represent a major challenge, while at the same time it offers also a great opportunity [8, 9].** In order to exploit the high number of existing and potential future customers, many companies have therefore established their own firm-sponsored online customer networks which are specialized, non-geographically bound digital communities focusing on company-relevant topics and products [10–13]. Participating customers actively interact with each other via different forms of social engagement activities such as posting or asking question [14]. These social engagement activities not only represent a lively **exchange about a company's products and services** among customers but also allows companies to analyze the nature, content, and sentiment **of customers' activities**. Companies strive to learn about the positive or negative sentiment of their customers towards the company, their products, or services [15, 16]. To learn about the hidden moods of their customers, companies demand advanced sentiment analysis techniques to deeply investigate **customers' social engagement activities [5, 17, 18].**

Recent studies have started to investigate the impact of social engagement in online customer networks on purchase intentions, financial risk-seeking tendencies, or profitability [10, 19–22]. However, due to the lack of sufficient content data, none of these studies were able to investigate social engagement activities and **the relationship between customers' sentiment and their revenues** in-depth. Thus, there is still a lack of knowledge about **customers' social engagement sentiment in online customer networks as well as about its impact on customers' revenues**. This research paper broadens existing research about **customers' social engagement sentiment** by analyzing a comprehensive dataset from the online customer network of a German direct banking institution. This dataset contains **customers' financial information** in form of credit card revenues in addition to information about customers' social engagement activities within the online customer network. The study aims to investigate the following research question: **What is the hidden sentiment of customers participating in an online customer network and what is the relationship between customers' sentiment and their revenues?**

By conducting an unsupervised lexicon-based sentiment analysis [18, 23], the sentiment of **customers' social engagement activities in the direct banking institution's online customer network** was determined. Thus, this research is, as one of the first, able to investigate the

hidden moods of active customers, **the relationship between customers' initial social engagement activities** (posts and questions) and their reactions to them (comments and answers) as well as the relationship of **customers' overall sentiment and their revenues**.

The remainder of the paper is organized as follows. The next section provides an overview of related literature, followed by the introduction of the dataset in Section 3. Section 4 presents the results of the sentiment analysis and the analysis of the relationship between **customers' sentiment and their revenues**. Section 5 discusses the key findings, limitations, and future research directions. Finally, in the last section, the paper concludes with a brief summary.

2 Theoretical Background

2.1 Social engagement in online customer networks

The research about social engagement activities in online customer networks is part of the general research about social media [6, 24, 25]. An online customer network is defined as a firm-sponsored, non-geographically bound, topic-focused online community, which enables participating customers to gather more detailed information about the company as well as to discuss product-related topics with other customers [11, 12]. Social engagement activities thereby include participating in discussion groups through posting and commenting or asking and answering questions with a focus on knowledge sharing and acquisition [14, 25–27]. By engaging customers in multiple forms of interaction, companies aim at strengthening long-lasting relationship with them [11, 14, 28]. The possibility to interact with each other via an online customer network is a tremendous improvement both for companies and customers compared to the former “**offline**” interaction, where a customer-to-company communication was mainly unidirectional and comparatively little exchange among customers [14, 29]. Therefore, the encouragement of an active customer participation is regarded as the key to establishing a successful online customer network [19, 30]. Additionally, **customers' active participation** in online customer networks is regarded as having an important **impact on customers' revenues** [7, 10, 19, 28]. Existing research, however, mostly focused on non-monetary aspects such as brand awareness, value co-creation, or customer behavior **when investigating the impact of customers' social engagement activities** [28, 31]. Only few studies have analyzed thus far the impact of social engagement on revenues [10, 19]. However, **neither of these studies were able to investigate customers' social engagement sentiment in detail or its relationship towards revenues**.

2.2 Sentiment analysis in the context of online customer networks

Customers' social engagement activities in online customer networks generate a constant flow of textual content in form of posts, comments, questions, or answers [5]. Via social engagement activities, customers share opinions, recommendations, and criticism with

other customers. Companies are able to gain insight into the strengths and weaknesses of their products and services and learn about their **customers'** hidden moods by analyzing the sentiment of the social engagement activities. However, the large amount of heterogeneous data poses a challenge to retrieving valuable information. On this account, the research about sentiment analysis provides suitable techniques for investigating large amounts of user-generated content [17, 18, 32, 33].

Sentiment analysis describes the process of extracting subjective information about individuals, such as sentiment, within large numbers of documents [17, 33, 34]. During the analysis process, a score is assigned to each textual entity to provide a tendency regarding whether the **author's** mood is positive, negative, or neutral [17, 33]. The context of application for sentiment analysis is **diverse and ranges from predicting customers' sales performances** and ranking products and companies, to analyzing huge amounts of user-generated content from online **communities to learn more about users' behavior** [33, 35–37]. There are two main approaches for sentiment analysis: supervised machine-learning analysis using a manually labelled training set [38] and unsupervised lexicon-based analysis utilizing a sentiment lexicon [17, 18]. While there is a broad range of literature about sentiment analysis in general, **few studies investigate customers'** sentiment in the context of online customer networks as well as the relationship between **customers'** sentiment and revenues. Existing studies merely focus on predicting future sales and buying behavior based on the results of a sentiment analysis [39, 40]. Therefore, there is a need for **in-depth analysis of customers'** sentiment in order to understand the hidden moods of active customers as well as its impact on **customers'** revenues.

2.3 Research gap and intended contribution

Customers' social engagement activities are regarded to have high impact on their revenues [19]. Thus, understanding the sentiment of **customers'** social engagement activities is of great importance for companies in order to enable a sustainable and effective operation of online customer networks. While research exists about general social media consumer behavior, there is little knowledge about **customers' sentiment** as well as the relationship **between customers' sentiment and their revenues**. Existing studies have focused so far on **customers' risk aversion or general online behavior** [20–22, 41]. Further studies analyzed the impact of different social engagement activities on **customers' behavior and profitability** [10, 19, 26]. However, **most studies are based on limited datasets about customers' social engagement and financial activities** [20, 41], lack a clear distinction between different forms of social engagement [10], or are based on a small sample [19, 26]. None were able to **investigate the content of customers' social engagement activities in detail**.

This research paper extends existing research based on the analysis of **customers' social engagement sentiment as well as the relationship between customers' sentiment and their**

revenues. It accomplishes this goal by analyzing a comprehensive dataset of the online customer network of a German direct banking institution including customers' financial information as well as data about customers' social engagement activities. Thus, it is among the first studies to analyze the content of active customers' social engagement activities by means of an unsupervised lexicon-based sentiment analysis, and thus performs an in-depth investigation of customers' social engagement sentiment as well as the relationship between customers' sentiment and their revenues. The research paper aims at broadening the understanding of customers' social engagement activities both for research and practice.

3 Case Setting and Data Collection

The online customer network of the German direct banking institution under observation is one of the biggest German communities focusing on financial topics with more than 500,000 registered users. The direct banking institution's product offerings range from standard financial products such as an overdraft loan to innovative and modern financial services and products such as crowd funding. Its online customer network forms the linchpin for the interaction between the direct banking institution and its customers as well as for the exchange of information among customers. Customers are able to discuss current finance-related topics, ask and answer questions, give feedback, and formulate their opinion about financial products. Summed up, customers share their knowledge with others, either in topic-specific forum groups or in a more general forum section.

Customers' social engagement in the form of written contributions is divided into four social engagement categories: 1) a post in a topic-specific forum group, 2) a comment to a post, 3) a question in the general forum section, and 4) an answer to a question. As displayed in Figure 1, posts and questions represent initial activities while comments and answers are corresponding reactions to these activities. For example, one customer's question in the general forum section can lead to multiple answers or to none.

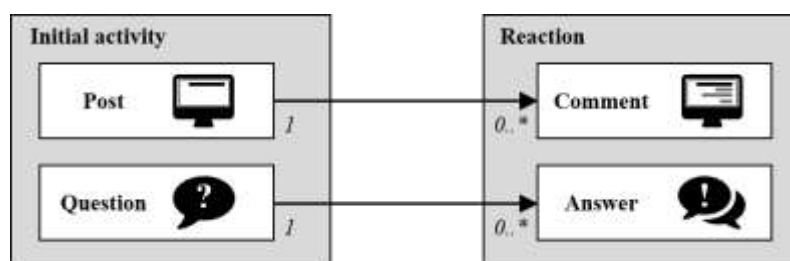


Figure 1. Social engagement categories

For this research paper, 525,510 registered customers were analyzed anonymously over the period from August 1, 2016 to August 31, 2017. The dataset comprises two parts (cf. Table 1): First, data was compiled on 5,295 active customers with social engagement activities during the period of observation including 3,336 customers who purchased at least one of the institution's products and therefore had revenue at the same time. Second, data was

drawn from 520,215 non-active customers without active participation which are merely passively consuming active customers' social engagement activities – a commonly observed phenomenon for online customer networks [14]. In total 64,509 customers with revenue were observed. Among them were 61,173 non-active customers.

Table 1. Active and non-active customers

<i>Customers</i>	<i>Active</i>	<i>Non-active</i>	<i>Total</i>
Customers with revenue	3,336	61,173	64,509
Customers without revenue	1,959	459,042	461,001
Total number of customers	5,295	520,215	525,510

To investigate the relationship between the revenue of active and non-active customers, a *Mann-Whitney U test* with the variable *revenues* and *active* (active = 1 vs. non-active = 0) was conducted [42]. The results indicate a significant difference between the revenue of active and non-active customers ($p < 0.01$). While active customers have a mean revenue of 6,778.37 EUR, non-active customers have merely a mean revenue of 6,335.46 EUR. As confirmed by previous studies, customers who have at least one social engagement activity are in general associated with higher revenues [10, 19, 20]. In the following, the two parts of the dataset are presented in detail. The first part comprises **customers' social engagement** activities (cf. Table 2). 5,295 active customers had at least one of the in total observed 75,596 social engagement activities. The average numbers of activities per customer and category reveal that posts and questions are made by various active customers, but the comments and answers are made by comparatively few.

Table 2. Customers' social engagement activities

<i>Category</i>	<i>Social engagement activities per category</i>	<i>Active customers per category</i>	<i>Avg. social engagement activities per customer and category</i>
Posts	1,883	918	2.05
Comments	11,694	1,047	11.17
Questions	8,086	3,493	2.31
Answers	53,923	3,067	17.58

The second part comprises **customers' financial information** in the form of the accumulated number of credit card transactions as well as the sum of revenue (cf. Table 3). The 3,336 active customers with revenues made in average 110.54 transactions and had average revenues of 6,778.37 EUR. In contrast, 61,173 non-active customers with revenues made in average 76.84 transactions and had average revenues of 6,335.36 EUR. In total, customers with revenues made 5,069,116 transactions and revenues of 410,165,313.90 EUR in total. These customer-specific financial data serve as the basis for the analysis of the relationship **between customers' sentiment and revenues and is neither limited** to a certain product nor customer segment, in contrast to existing studies [10, 26].

Table 3. Customers' financial data

		<i>Active customers (3,336)</i>	<i>Non-active customers (61,173)</i>	<i>Total (64,509)</i>
Revenues	Sum [EUR]	22,612,633.13	387,552,680.77	410,165,313.90
	Avg. [EUR]	6,778.37	6,335.36	6,358.26
	Min. [EUR]	0.01	0.01	0.01
	Max. [EUR]	227,953.60	1,662,780.69	1,662,780.69
Number of transactions	Sum	368,766	4,700,350	5,069,116
	Avg.	110.54	76.84	78.58
	Min.	1	1	1
	Max.	1,008	2,354	2,354

Although there are fewer active customers than non-active customers, the share of the 3,336 active customers with revenues among all 5,295 active customers with 63.00%, which is more than 5 times higher compared to the share of the 61,173 non-active customers with revenues among all 520,215 non-active customers. In addition, while the total sum of revenues of the non-active customers is higher, the average of both the revenues as well as the number of transactions is higher for active customers compared to non-active customers. This indicates that active customers – although in the minority – have a far higher number of transactions and that the resulting revenues are in average higher compared to non-active customers.

4 Data Analysis and Findings

4.1 Analyzing customers' social engagement sentiment

The sentiment of the 75,586 social engagement activities of all participating customers was analyzed using an unsupervised lexicon-based approach which is suitable for the analysis of huge amounts of content data [18, 33]. For this approach, each entity within a document is compared to a given sentiment lexicon and the corresponding sentiment value is added to the **document's** overall sentiment value. The basic processing steps for the lexicon-based approach are 1) **preprocessing in form of removing "noisy" characters such as HTML tags**, 2) initialization of the document sentiment score S ($S \leftarrow 0$), 3) analyzing whether the entity is positive (S^+) or negative (S^-), and 4) evaluating the final sentiment score S ($S = S^+ - S^-$) of the document [18, 43]. By using the data analytics platform *KNIME* and the *GermanPolarityClues* sentiment lexicon [23], each social engagement activity was labelled either as positive, negative, or neutral. A social engagement activity was thereby considered to be positive when the number of positive identified entities in the document was higher than the number of negative identified entities and vice versa. Activities with no clear positive or negative sentiment were labelled as neutral [43, 44]. Table 4 provides an overview of the results of the sentiment analysis. Overall, the share of positively rated social engagement activities is higher than the share of negatively rated ones. Furthermore, comments on posts

have, contrary to the general trend, a higher share of negatively labelled documents than of positively labelled ones. In contrast, for example, answers to questions tend to have a much more positive than negative sentiment. However, the majority of all social engagement activities are labelled as neutral.

Table 4. Sentiment analysis per social engagement category

	<i>Posts</i>		<i>Comments</i>		<i>Questions</i>		<i>Answers</i>		<i>Total</i>	
	#	%	#	%	#	%	#	%	#	%
Positive	431	22.89	1,516	12.96	1,449	17.92	8,037	14.90	11,433	15.12
Negative	222	11.79	1,722	14.73	598	7.40	4,205	7.80	6,747	8.93
Neutral	1,230	65.32	8,456	72.31	6,039	74.68	41,681	77.30	57,406	75.95
Total	1,883	100.00	11,694	100.00	8,086	100.00	53,923	100.00	75,586	100.00

4.2 Analyzing the sentiment of customers' initial activities and reactions

Customers' social engagement activities during the period of observation are either initial activities (posts or questions) or reactions to them (comments or answers) (cf. Figure 1). To investigate whether there are differences in sentiment between customers' initial activities and the reactions to them, a detailed analysis of customers' social engagement activities is displayed in Table 5 and Table 6. The significance of the differences is confirmed by the *Chi-Square Test of Independence* ($p < 0.01$) [45].

The analysis indicates that the majority of all social engagement categories are labelled as neutral. However, when focusing merely on positively or negatively labelled reactions, the initial activity's sentiment is also observed in the reaction(s) to it. For example, the 222 posts with a negative sentiment are subsequently followed by a significantly higher share of negative comments rather than by positive comments (cf. Table 5). Therefore, the initial negative sentiment of customers' social engagement activities also dominates in the subsequent reactions to it. This is similarly observed with the 1,449 positive questions, which receive a significantly higher share of positive answers compared to negative answers (cf. Table 6). A difference can be observed for the reactions to neutral posts and questions. The reactions to the 1,230 neutral posts have a significantly higher share of negative comments compared to positive comments (cf. Table 5). On the contrary, the share of negative answers to the 6,039 neutral questions is significantly lower compared to positive answers (cf. Table 6). Therefore, there is not only a difference between customers' initial social engagement activities and the reactions to them but also between the different social engagement categories.

Table 5. Customers' initial posts and the reactions in form of comments

Posts (#)	Comments						
	Positive		Negative		Neutral		Σ
	#	%	#	%	#	%	#
Positive (431)	510	16.54	419	13.59	2,154	69.87	3,083
Negative (222)	239	12.31	303	15.61	1,399	72.08	1,941
Neutral (1,230)	767	11.50	1,000	14.99	4,903	73.51	6,670

Table 6. Customers' initial questions and the reactions in form of answers

Questions (#)	Answers						
	Positive		Negative		Neutral		Σ
	#	%	#	%	#	%	#
Positive (1,449)	2,192	20.50	744	6.96	7,756	72.54	10,692
Negative (598)	485	11.20	581	13.42	3,264	75.38	4,330
Neutral (6,039)	5,360	13.78	2,880	7.40	30,661	78.82	38,901

4.3 Analyzing customers' sentiment in relation to their revenues

To investigate the relationship between customers' sentiment and their revenues, each of the 3,336 active customers with revenue during the period of observation are assigned to a positive, negative, or neutral sentiment group. The sentiment group is determined based on the calculation of an overall sentiment score $S_{(c)}$:

$$S_{(c)} = S^+_{(c)} - S^-_{(c)} \quad (1)$$

The sentiment score $S_{(c)}$ represents the sum of all positively labelled entities $S^+_{(c)}$ attributed to customer c minus the sum of all negatively labelled entities $S^-_{(c)}$ [43, 44]. Therefore, the overall trend of a customer's sentiment is deduced, and the customer accordingly assigned to the positive sentiment group when $S_{(c)} \geq 1$, negative sentiment group when $S_{(c)} \leq -1$, or neutral sentiment group when $S_{(c)} = 0$. Furthermore, the sentiment scores are related to the number of transactions as well as to the sum of revenues. The results of the Spearman rank correlation analysis to measure the strength and direction of the association between customers' overall sentiment and their revenues reveal a significant ($p < 0.05$) negative correlation [46]. More than half of the active customers belong to the positive sentiment group, followed by the customers in the negative sentiment group, and the customers in the neutral sentiment group (cf. Table 7). Accordingly, customers in the positive sentiment group also have the highest share of transactions among all active customers and the highest sum of revenues. However, there is a striking difference in the average revenues per customer: Customers in the negative sentiment group have significantly higher average revenues compared to customers in the positive sentiment group as well as customers in the neutral sentiment group.

Table 7. Relationship between active customers' sentiment and their revenues

Sentiment group	Number of active customers		Number of transactions		Total revenues		Avg. revenues
	#	%	#	%	[EUR]	%	[EUR]
Positive	1,847	55.37	199,923	54.21	12,391,485.02	54.80	6,708.98
Negative	944	28.30	112,389	30.48	6,792,144.71	30.04	7,195.07
Neutral	545	16.34	56,454	15.31	3,429,003.40	15.16	6,291.75
Total	3,336	100.00	368,766	100.00	22,612,633.13	100.00	6,778.37

5 Discussion, Limitations, and Future Research

5.2 Discussion and implications for theory and practice

Based on the dataset from the online customer network of a German direct banking institution, this research was able to analyze the sentiment of more than 75,000 social engagement activities. The aim is to help practitioners to better understand customers participating in online customer networks **as well as the relationship between customers' sentiment and their revenues**. Overall, the contribution of this paper to theory and practice is threefold:

First, the sentiment of customers' social engagement activities is in general more positive than negative (cf. Table 4). While in sum 15.12% of all activities are labelled with a positive sentiment, merely 8.93% are negatively labelled. Although most of the investigated activities are labelled as neutral, the positively and negatively labelled activities contain the most interesting information about the overall atmosphere within the online customer network [43, 47]. A detailed analysis of the individual social engagement categories confirms the general positive trend for posts, questions, and answers with the exception of comments where the share of negatively labelled activities is higher than that of the positively labelled ones. This exception indicates a more controversial discussion in the topic-specific forum groups compared to the general forum section. However, a critical discussion does not necessarily have negative implications for the sponsoring company. Rather, it can lead to an animated and lively exchange of opinions and information and thus support **customers' decision-making processes** [48]. Existing literature in general considers a positive sentiment **of customers' social engagement activities** as more beneficial in both financial and non-financial terms [25]. Positive social engagement activities affect customer loyalty positively, strengthens the relationship between customer and company, and leads to increased revenues [14]. Companies should therefore encourage customers with positive sentiment to participate more actively in their online customer networks but also carefully monitor customers with negative sentiment. In any case, a long-term investigation into whether these customers contribute to a lively discussion culture or are harmful with regards to the growth **of customers' revenues** is necessary.

Second, the sentiment of an initial social engagement activity has an important influence on customers' subsequent activities. When looking at the sentiment of customers' reactions to initial activities, a general continuation of the initial activity's sentiment in the reaction's sentiment can be observed when focusing merely on positively or negatively labelled activities. Therefore, the initial social engagement activity is important due to its significant influence on customers' subsequent activities. The share of positive comments subsequent to positive posts is higher compared to the share of negative comments. This becomes even clearer when looking at positive questions and the much higher share of subsequent positive answers compared to negative answers. The same relationship between the initial social engagement activity and subsequent reaction(s) can be observed for the initially negative posts (cf. Table 5) and negative questions (cf. Table 6). The stringent sentiment succession indicates the influence of customers' initial activities and is in line with current research about the emotional contagion of social media users [4, 43]. Encouraging more customers to participate in positive initial social engagement activities will at the same time increase positive reactions and will therefore lead to an overall positive sentiment within online customer networks [43, 47]. Moreover, the reaction to neutral posts and questions is interesting. While significantly more negative comments than positive comments are followed by neutral posts (cf. Table 5), significantly more positive answers compared to negative answers in reaction to initially neutral questions were observed (cf. Table 6). This is in line with the previous observations about the controversial discussion culture in the topic-specific forum groups. However, the relatively strong positively labelled reactions to neutrally labelled questions indicate a general willingness to help each other within the group of active customers [4]. Practitioners should carefully ensure that customers' initial social engagement activities have a positive sentiment, as it encourages positive reactions by other customers. Thus, a positive overall sentiment can be achieved, which in turn supports the companies' aim of increasing customers' loyalty as well as their revenues [14].

Third, customers with a positive overall sentiment score are surprisingly not the main drivers for revenues. While the majority of all active customers with revenues belong to the positive sentiment group, the minority belongs to the negative sentiment group (cf. Table 7). However, comparing the individual sentiment score with customers' revenues leads to surprising results: The customers in the negative sentiment group have a significantly higher average revenue compared to the customers in the positive sentiment group. These results contradict general expectations that customers with a positive sentiment also have higher revenues [14]. To the contrary, they reveal that customers from the negative sentiment group are the main drivers for revenues. These customers can be valuable for two reasons: First, negative and critical social engagement activities enliven discussions, since they are more likely to trigger participation from other customers [47]. Second, despite an overall negative sentiment score, these customers generate more revenues compared to other customers.

The results of this research indicate that companies should on the one hand avoid a negative, possibly business-damaging overall atmosphere **created especially by customers' initial** social engagement activities with a negative sentiment. On the other hand, companies should focus on establishing a lively discussion culture without restricting customers too much regarding their online social engagement activities. This includes tolerating activities with a negative sentiment and at the same time increasing customers' affection towards the online customer network. This research has shown that customers with a negative overall sentiment at the same time have higher revenues and are more valuable to the investigated institution compared to positive or neutral customers. Therefore, instead of trying to completely avoid negative social engagement activities in their online customer network, companies should focus on keeping a reasonable balance in order to also encourage customers from the positive or neutral sentiment groups to increase their revenues.

5.2 Limitations and future research directions

This research provides a comprehensive analysis of **customers' social engagement activities** sentiment. However, there are limitations which can act as a starting point for future research.

First, although this research is based on a dataset comprising extensive social engagement activities as well as financial data over a period of more than one year, it is limited to one single online customer network from the financial domain. For future research, the analysis of social engagement activities from more than one online customer network is desirable for identifying similarities, differences, or industry-specific peculiarities.

Second, the observed correlation **between customers' sentiment and their revenues** is, although significant, not very strong. Besides customers' social engagement activities' sentiment, there are many other influencing factors on customers' revenues such as historical behavior or personal income. However, this research focused particularly on the detailed **analysis of the sentiment of customers' social engagement** activities in the context of online customer networks. Thus, it is not able to provide an overall forecasting model for customer revenues, but might serve as a benchmark for future research.

Third, the focus is on credit card revenues while other sources of revenues, such as purchases of shares and bonds, were neglected. Although the available financial data are comprehensible and complete, there is a broader perspective generally on customer revenues and inclusion of all relevant customer revenues should be the focus of future research.

Finally, sentiment analysis is a complex process of determining the polarity of a given entity. However, there are still difficulties in recognizing sarcasm, irony, or slang [32, 38]. Context-specific sentiment lexicons in combination with an extensive training set might help to overcome these difficulties, however, even human interpreters agree only in 80% of all cases

on the same sentiment [44]. Hence, **determining customers' sentiment** is most often never clear-cut and can depend on the specific context. **Future research about customers' social engagement sentiment** should focus on developing more robust sentiment analysis approaches.

6 Conclusion

The huge amount of user-generated content represents both a curse and a blessing for companies. In particular, companies hosting their own firm-sponsored online customer networks are facing a greater number of challenges and are struggling to take advantage of the available data about their customers' **social engagement activities** [33]. The research on social engagement activities in online customer networks is therefore important for practitioners as well as researchers [10, 19, 20]. This research contributes to the existing literature by focusing on a **detailed analysis of customers' social engagement sentiment as well as the relationship between customers' overall sentiment and their revenues**. In this context, sentiment analysis is considered as an effective method to analyze the ever increasing amount of data occurring in online customer networks [17]. The available dataset of the German direct banking institution comprises data about customers' **social engagement activities and their financial data** over a period of over one year. Applying a lexicon-based sentiment analysis, several interesting findings are observed. First, the share of positively labelled social engagement activities is higher compared to the share of negatively labelled ones, which indicates a general positive atmosphere within the online customer network. Second, the **sentiment of customers' initial activities is often mirrored in the reactions to them**. This indicates a general willingness of active customers to help each other. Third, customers with an overall negative sentiment score at the same time have surprisingly higher revenues compared to customers with an overall positive or neutral score. Therefore, although more critical and negative in nature, they seem to be valuable to the company. By investigating this hidden moods of customers, the knowledge about **customers' social engagement activities** in online customer networks is broadened and extended. Furthermore, this research aims at supporting companies in successfully managing their online customer networks and increasing future customer revenues. Beyond that, it hopes to stimulate future research about the interesting research area of social engagement in online customer networks.

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3 Network-Oriented Customer Valuation

Topic 2 – as the second part of the dissertation – is the focus of this chapter. Two papers deal with the research questions RQ.4 and RQ.5. The fourth paper of the dissertation, published in 2017 in the *Electronic Markets* journal, develops an approach for a network-oriented valuation of customer participating in online social networks (RQ.4). Finally, the fifth paper, published in the proceedings of the 2017 International Conference on Information Systems, extends this novel approach by including besides positive also negative network effects into the calculation (RQ.5). Both papers presented in this chapter deal with the **network-oriented valuation of customers' value in the context of online customer networks** by developing, presenting, and demonstrating novel approaches in this area.

3.1 Customer Lifetime Network Value: Customer Valuation in the Context of Network Effects

No.	Title	Full Citation	Year	Status
4	Customer Lifetime Network Value: Customer Valuation in the Context of Network Effects	Däs, M., J. Klier, M. Klier, G. Lindner and L. Thiel (2017). "Customer lifetime network value: customer valuation in the context of network effects" <i>Electronic Markets</i> 27 (4), 307–328.	2017	Accepted

Abstract

Nowadays customers are increasingly connected and extensively interact with each other using technology-enabled media like online social networks. Hence, customers are frequently exposed to social influence when making purchase decisions. However, established approaches for customer valuation mostly neglect network effects based on social influence. This leads to a misallocation of resources. 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 customers' net contribution to the network, the CLNV reallocates values between customers based on social influence. Inspired by common prestige- and eigenvector-related centrality measures it incorporates social influence among all degrees of separation acknowledging its viral spread. Using a real-world dataset, we demonstrate the practical applicability of the CLNV to determine individual customers' value.

Keywords: Customer Valuation, Customer Lifetime Value, Social Influence, Network Effects.

Introduction

“We went from a connected world to a hyperconnected world” (Friedman 2013). Today, with around half of the world’s population online, people are ever more closely connected and therefore interact to a great extent with each other using technology-enabled media (ITU 2016). In fact, the number of users of online social networks (OSNs) worldwide is expected to rise from over 2 billion in 2016 to almost 3 billion in 2020 (eMarketer 2014, 2016). The large number of digitally connected people exerts a great impact on all areas of life and companies can no longer ignore this revolutionary transformation of business and society with regard to future business success (e.g., Bond et al. 2012). Marketers therefore see social marketing and digital commerce as the top areas of future technology investment (Gartner Group 2015). By the rising number of connected customers, extensive social influence, for example through word-of-mouth (WOM), is exerted and dispersed with previously unknown reach, intensity, and speed. Consumer surveys reveal that up to 88% of online customers see WOM as the most trustable form of product recommendation (Nielsen 2015) and many customers rely on WOM when searching for information about products or services (Moon et al. 2010) or making purchase decisions (Chen and Xie 2008). In fact, especially in the younger generation around 85% of consumers naturally use OSNs for product research to gather information for their purchase decisions (Butler 2017; Solomon 2015). Furthermore, consumers more and more recommend products and companies via OSNs and also rely heavily on the recommendations of other consumers when it comes to purchase decisions (Chen and Xie 2008; Lis and Neßler 2014; Solomon 2015). This remarkable importance of customer-to-customer interactions has been on the one hand intensively discussed in prior research (Algesheimer and von Wangenheim 2006; Libai et al. 2013; McAlexander et al. 2002; Rossmann et al. 2016). On the other hand, marketers state that WOM in social media is of particular relevance for their marketing activities and that they expect a strong growth of around 70% of marketing expenditures in this area in nearer future (WOMMA 2014). With respect to customer valuation, it is consequently crucial for companies to evaluate customers not isolated from each other but in a network context. For instance, think of customers who do not purchase anything but whose social influence induces purchases of several other customers. When neglecting network effects, such customers would be valued as unprofitable and would be ignored in a company’s strategic decisions, although these customers do in fact add value to the company. An increase of the OSN share in the marketing budget up to 20% reveals the recognized importance of social media by marketers (The CMO Survey 2016).

Even though research has dealt extensively with customer valuation (Berger and Nasr 1998; Dwyer 1997), network effects in customer valuation have not been sufficiently investigated yet. Only very few studies started to address selected aspects of network effects in general

customer valuation models (Domingos and Richardson 2001; Hogan et al. 2003). Also, regarding 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 consider only direct network effects (i.e. influence among the first degree of separation) hence ignoring the viral spread of social influence inside a network beyond the first degree of separation (Klier et al. 2014) and/or concentrate on including network effects incentivized through referral campaigns (Kumar et al. 2007; 2010a; Lee et al. 2006) or other marketing and seeding programs (Hogan et al. 2004; Kumar et al. 2013; Libai et al. 2013) by compensating recommendations with a higher customer value. Further studies extend **the CLV by increasing a customer's value based on network aspects arising** outside of incentivized programs (Kumar et al. 2010a; Weinberg and Berger 2011). However, to the best of our knowledge, so far none of these studies has considered direct and indirect network effects in conjunction with the mirror-inverted effect yet: besides customers creating value in a network due to their direct and indirect influence on others, **customers may also "owe"** value to the network due to the social influence of other customers on their cash flows. Models neglecting this mirror-inverted effect are subject to double counting, as the additional value component representing network effects is once considered for the customer **inducing other customers' cash flows and once for the customers actually generating these** cash flows. In consequence, both double counting and the negligence of indirect network effects in existing customer valuation models lead to a misvaluation of individual customers **and the whole customer base (i.e. a firm's customer equity (CE)), resulting, for example, in** suboptimal (marketing) decisions and strategies.

Therefore, following a design-oriented approach (Hevner et al. 2004), the aim of this paper is to develop a novel model for customer valuation incorporating an integrated network perspective referred to as the customer lifetime network value (CLNV). We determine the value of a customer based on the *present value of the individual cash flows* generated by him/her and the *present value of his/her net contribution to the network*. The CLNV is inspired by prestige- and eigenvector-related centrality measures like Katz prestige (Katz 1953) or the PageRank algorithm (Brin and Page 1998), thereby acknowledging the viral characteristic of networks. We demonstrate the applicability of the CLNV using a real-world case of a European OSN focusing on sports. 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 allows an allocation of not only direct but also indirect network effects inside a network; and third, it facilitates a sound **determination of a company's CE as the sum of all customers' CLNVs.**

The 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. Afterwards, the applicability of the CLNV is demonstrated by using a

real-world case of a European OSN focusing on sports. Finally, we give a brief summary and conclude with a discussion on limitations and directions for further research.

Literature Background

Online Customer Networks and Social Influence

Due to technology-enabled media, people are increasingly connected and extensively interact with each other. Against this background, companies face the challenge that customers can no longer be regarded as isolated individuals. Rather, customers are parts of (online) social networks enabling them to interact across personal and regional boundaries. Similar to social networks in general (Adamic and Adar 2003; Bampo et al. 2008; Kane et al. 2014; Wasserman and Faust 1994) online customer networks can formally be represented by a graph consisting of a set of nodes (representing the customers) and a set of edges (representing relations or interactions between pairs of customers).

Various studies have found the behavior of members in offline and online networks to be affected by social influence from other members in the network (Probst et al. 2013). Hereby, social influence can be induced through different forms of interactions, such as one-to-one or one-to-many WOM, observation and/or imitation, and information sharing with advice-seeking individuals (Arndt 1967; Herr et al. 1991; Iyengar, Van den Bulte and Valente 2011; Kumar et al. 2010a; Libai et al. 2013; Nitzan and Libai 2011; Wangenheim and Bayón 2007). Five causes of social influence in networks are discussed in literature (Hinz et al. 2014; Iyengar, Van den Bulte and Valente 2011; Kane et al. 2014; 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 (Katz and Lazarsfeld 1955). Second, information about costs and benefits of actions reduces search efforts and uncertainty and therefore increases adaption (Iyengar, Van den Bulte and Choi 2011). Third, normative pressure to fulfill the expectations of others (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, i.e., with every additional customer consuming a good the value of consuming this particular good increases (Granovetter 1978; Katz and Shapiro 1994).

Many authors focus on direct social influence, i.e., influence between two users that directly interact with each other (e.g., Klier et al. 2014). However, social influence in OSNs does not stop at the first degree of separation as it takes place with an extended scope, speed, complexity, and independent of time and place (Gruzd and Wellman 2014). To the contrary, content can spread “virally” through the entire network (Hogan et al. 2004; Nahon and Hemsley 2013). Thus, it affects not solely the users directly, but also indirectly connected to the source. Such indirect influence, sometimes called the “ripple effect” (Hogan et al. 2004; Oestreicher-Singer et al. 2013), has been subject of research in context of offline social

networks (Granovetter 1973; Harary et al. 1965) as well as OSNs (Goldenberg et al. 2009; Gruzd and Wellman 2014; Hinz et al. 2011; Hogan et al. 2004; Kiss and Bichler 2008). However, despite the viral diffusion of information in networks as a whole, research on indirect effects is often limited to influence at the first degree of separation (Gruzd and Wellman 2014). Recent studies, for instance Gruzd and Wellman (2014), therefore demand and predict a shift from social one-to-one influence to a more network-centric view, called **“networked influence”** (Gruzd and Wellman 2014, p. 1255).

Prior research shows that social influence, both direct and indirect, is of high practical relevance for companies: On the one hand, connections between customers can be used for referrals. Hence, social influence can help companies to acquire new customers at relatively low acquisition costs (Kumar et al. 2007; 2010a, b; 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 “belief, attitude, or behavior”** of existing customers (Erchul and Raven 1997, p. 138), including their purchase decisions and loyalty (Algesheimer and von Wangenheim 2006; Hogan et al. 2004; Kumar et al. 2010a; Nitzan and Libai 2011; Soares and Pinho 2014; 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; Gruzd and Wellman 2014; Heidemann et al. 2010; Hinz et al. 2011; Trusov et al. 2010; Zhang et al. 2011). Recent research has highlighted that, in addition to customer characteristics such as age, gender, education, and expertise (Aral and Walker 2012; de Valck et al. 2009; Eccleston and Griseri 2008; Gladwell 2000; Katona et al. 2011; Watts and Dodds 2007; Zhang et al. 2011), **the structure of the network can affect a customer’s influence on other customers. In this context, a customer’s connectivity, for example his/her number of direct or indirect connections, is shown to affect a customer’s influential power** (Algesheimer and von 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 social influence, customers’ communication activities or interactions are increasingly** used to identify influencers (Cheung and Lee 2010; de Valck et al. 2009; Heidemann et al. 2010; Kane et al. 2014; Mtibaa et al. 2010). To take into account the entire network structure when identifying influencers, several authors have started to implement approaches based on prestige- and eigenvector-related centrality measures like Katz prestige (Katz 1953), Bonacich centrality (Bonacich 1972), or the PageRank algorithm (Brin and Page 1998) (cf. e.g., Heidemann et al. 2010; Kiss and Bichler 2008; Mtibaa et al. 2010). Their approaches use iterative calculations to quantify a user’s influence in a network based on **the users’ connections in the network.**

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, a customer's value should not solely consider the cash flows generated by him/her (e.g., through purchases) but also the network effects in terms of his/her direct and indirect social influence on the cash flows of others in the network (e.g., through WOM) and vice versa.

Customer Valuation and Network Effects

Customer valuation has been subject of extensive prior research (Berger and Nasr 1998; Kotler and Armstrong 1996). The classic CLV constitutes one of the most well-known customer valuation models. It 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 a company is expecting to earn with a customer over his/her lifetime therefore reflecting all monetary and non-monetary aspects like customer satisfaction which some day find expression in the customer's cash flows (Gupta et al. 2006). The CLV and its various adaptations have proven useful in a variety of contexts such as segmenting customers, optimizing the timing of product offerings, evaluating competitor companies, or supporting merger and acquisition decisions (Kumar et al. 2004; 2008; Venkatesan and Kumar 2004).

However, recent studies (Verhoef and Lemon 2013) show that it is essential to consider network effects in customer valuation. Indeed, a **customer's value can no longer be based solely on a customer's purchase behavior**. Rather, a customer's contribution to a company goes beyond direct transactions and includes elements like the value of social influence (Domingos and Richardson 2001; Hogan et al. 2003; Klier et al. 2014; Kumar et al. 2010a; Malthouse et al. 2013; Weinberg and Berger 2011). Against this background, few authors started to address selected aspects of network effects in general customer valuation models (Domingos and Richardson 2001; Hogan et al. 2003). Hogan et al. (2003), for instance, incorporate direct and indirect network effects when assessing the value of a lost customer using a product growth model. They argue that a company losing a customer does not only lose his/her future cash flows but also the cash flows of other customers due to slower customer acquisition resulting from reduced social influence. Another example is the work of Domingos and Richardson (2001) who model a Markov random field distinguishing two **components: the customer's intrinsic value representing the value s/he generates individually via 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 (Hogan et al. 2004; Kumar et al. 2007; 2013; 2010a, b; Lee et al. 2006; Libai et al. 2013; Weinberg and Berger 2011). Thereby, most of the studies focus on network aspects arising in campaign contexts, i.e., incentivized through marketing campaigns or seeding programs (Hogan et al. 2004; Kumar et al. 2007; Kumar et al. 2013; Kumar, Petersen et al.

2010; Lee et al. 2006; Libai et al. 2013). Lee et al. (2006) and Kumar et al. (2007), for instance, take account of social influence in form of referral campaigns (Kumar et al. 2007; Kumar, Petersen et al. 2010). When valuating a customer, these studies consider the original cash flows generated by a customer (as in the classic CLV) and add a second component, **often called “customer referral value” (CRV), covering cash flows of other customers that have been induced by him/her through a referral.** Lee et al. (2006) consider a customer’s original cash flows as well as the savings in acquisition costs for new customers obtained **through that customer’s social influence.** Kumar et al. (2007) estimate a customer’s referral value by determining either the entire transaction value (i.e., the net present value of all future cash flows and the savings in acquisition cost) or solely the savings in acquisition cost for customers who would not have joined the company without his/her referral (Kumar et al. 2007; Kumar, Petersen et al. 2010). Both Lee et al. (2006) and Kumar et al. (2007) focus on direct network effects considering only referrals among the first degree of separation (like Klier et al. (2014)). In addition, Hogan et al. (2004), Libai et al. (2013), and Kumar et al. (2013) measure the value of WOM incentivized through advertising or seeding programs. While Libai et al. (2013) establish the value of entire WOM-seeding programs using agent-based modeling, Hogan et al. (2004) determine the value of individual customers in context of WOM by adding all cash flows of other customers in the network induced by their WOM **to these customers’ CLV. Both studies acknowledge the fact that WOM spreads deep inside a network (i.e. beyond the first degree of separation).** The approach of Libai et al. (2013), however, does not allow for a definite determination of indirect network effects. Kumar et al. (2013) measure the monetary impact of (incentivized) WOM by, first, identifying influencers based on historical data, second, encouraging those influencers with incentives to share their opinion, and third, determining the value of influence for each customer. Hereby, **a customer’s value of influence is composed by the CLV of all people that are influenced by him/her (“influencees”) and, incorporating indirect network effects, a share of the cash flows those influencees received for influencing others.**

Next to that, further studies have implemented CLV-based approaches measuring social influence in non-campaign contexts, i.e., arising outside of incentivized marketing campaigns or seeding programs (Kumar et al. 2010a; Weinberg and Berger 2011). For example, **Kumar et al. (2010a) introduce the “customer influencer value” as a value component comprising all network effects that are not formally incentivized by a company.** For instance, effects occurring due to regular user interaction in social media are included. They quantify the customer influencer value based on a customer’s number of connections, the strength of those connections, and the “emotional valence” of the customer’s interactions (Kumar et al. 2010a, p. 302). They do, however, not focus on social influence “beyond the close social network” of a customer (Kumar et al. 2010a, p. 301). 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". The latter is determined by multiplying the CLV with impact factors considering the influential power and the customer's respective engagement level for each social medium used. They thereby include solely direct social media based non-incentivized effects (Weinberg and Berger 2011).

Summing up, previous studies have started to consider selected aspects of network effects in customer valuation. They emphasize that besides the cash flows generated by a customer when purchasing products or services, a customer's value should also consider the effect of his/her social influence on the cash flows of other customers in the network. To do so, previous work suggests adding further value components to the classic CLV representing the value of positive network effects.

Research Gap

Prior studies have started to include the relevance of customers with high social influence on other customers in customer valuation. However, they have not considered the mirror-inverted effect yet: besides customers creating value in the network due to their influence on others, customers may also "owe" value to the network due to the social influence of others on their purchasing behaviors. Hence, existing models are subject to double counting, as the additional value component representing the network effects is considered multiple times – once for the customers inducing other customers' cash flows and once for the customers actually generating these cash flows. Overestimating the value of a customer (e.g., due to double counting when calculating his/her CLV) might lead to wrong decisions. For example, potential new customers might be acquired or existing customers might be bound at too high cost (exceeding their "true" value for the firm). Indeed, double counting is a serious issue if it is important to have a best possible indication regarding the "true" value of a customer for the firm. Several studies have acknowledged that their approaches cause double counting (2010; Kumar, Petersen et al. 2010; Weinberg and Berger 2011). Kumar et al. (2010a, p. 308), for example, recognize that "[a]lthough CLV and CRV 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 value] is greater than the sum of all customers' CLV" (Weinberg and Berger 2011, p. 342). Next to that, with regard to the diffusion of social influence in networks, only a few studies have started to acknowledge indirect network effects when valuating customers. Consequently, most of the existing valuation models underestimate the true value of customers' influence beyond the first degree of separation (Klier et al. 2014; Kumar et al. 2007) and at the same time overestimate the value of customers being the intermediaries of those. Besides, even fewer studies provide an actual method to allow

the computation of indirect network effects. In fact, we found only two CLV-based approaches (Hogan et al. 2004; Kumar et al. 2013) enabling an allocation of both direct and indirect network effects in customer valuation.

Modeling the Customer Lifetime Network Value

Basic Setting

We consider a network of interlinked customers. The network can be represented by a set of nodes and a set of directed and weighted edges. Each node represents a customer and each edge represents the direction and strength of influence between a pair of customers, for example induced by WOM spread through private messages (Adamic and Adar 2003; Bampo et al. 2008; Heidemann et al. 2010; Hinz et al. 2011) or other sorts of user interaction. Customers in the network can generate cash flows through purchases. The existence and amount of these cash flows, however, may depend on the influence of other customers in the network. Note that the influence between two customers can be direct as well as indirect. Indirect influence exists when customers, who have been influenced by another customer, again influence others.

To illustrate the setting, we use an example of a network of four customers (1, 2, 3, and 4) who generate cash flows and positively influence each other both directly and indirectly (cf. Figure 1). The size of a node represents the amount of cash flows generated by a customer. Direct influence between a pair of customers is visualized by an edge between two customers. The direction of the edge represents the direction of influence; the size of the edge characterizes the strength of influence. Indirect influence between two customers is represented by two or more edges forming a path (e.g., from customer 3 to customer 4 via customer 2).

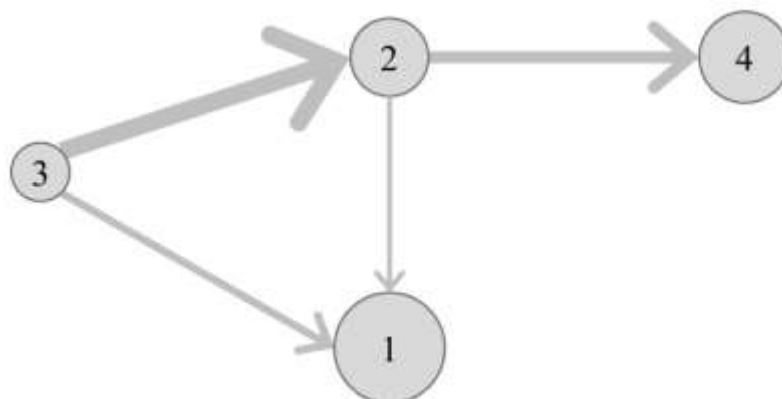


Fig 1 Illustration of a Customer Network

First, we consider direct network effects. Both customers 2 and 3 exert direct influence on customer 1. Thus, parts of the cash flows generated by customer 1 might depend on the

influence of customers 2 and 3, i.e., they might not have been generated without their positive influence. Consequently, the value of customer 1 would be overestimated when solely looking at the cash flows generated individually by him/her. At the same time, a **customer's value can be underestimated when regarding his/her cash flows** as isolated (Domingos and Richardson 2001; Hogan et al. 2003; Weinberg and Berger 2011). Customer 3, for example, might highly influence customers 1 and 2. Hence, the value of customer 3 within this network might be higher than indicated by his/her individually generated cash flows. Second, we can observe not only direct but also indirect influence in the customer network. Customer 3 directly influences customer 2, who again exerts direct influence on customer 4. Thus, along this path, customer 3 might indirectly influence customer 4. **Parts of customer 4's cash flows may therefore not only depend on the influence of customer 2,** but also on the influence of customer 3. Hence, considering solely direct influence would lead to an overestimation of the value of customer 2 and an underestimation of the value of customer 3. This rather straight forward example already shows that enhancing classic valuation methods (Berger and Nasr 1998) by accounting for not only direct (Klier et al. 2014) but also indirect influence of customers is crucial for companies, as ignoring such **network effects when deciding "which customer to market to can lead to severely suboptimal decisions"** (Domingos and Richardson 2001, p. 57).

Basic Idea

The aim of this paper is to develop an approach for valuating customers in the presence of direct and indirect network effects induced by the influence among customers. As a starting point, we assume the structure of the customer network (i.e., the number of nodes and the directed and weighted edges) **and each customer's cash flows as given. To calculate the CLNV,** we divide the customer value into two components: (1) the *individual cash flows* generated by him/her individually and (2) a network component incorporating direct and indirect network effects, which represents his/her net contribution to the network, referred to as Δ *network contribution*:

$$\begin{aligned} \text{CLNV} = & \textit{present value of individual cash flows} \\ & + \textit{present value of } \Delta \textit{ network contribution} \end{aligned}$$

Compared to previous studies that have started to include network effects in customer valuation (Kumar et al. 2007; 2010a, b; Libai et al. 2013; Weinberg and Berger 2011), our network component, Δ *network contribution*, differs out of two reasons: First, while previous work simply includes the effect a customer has on the network, our approach proposes to consider the mirror-inverted effect as well, i.e., the effect the network has on the customer. **Thus, we are not solely increasing a customer's value when s/he is exerting influence on others,** our approach also decreases a **customer's value when his/her cash flows are induced by the influence of others.** In contrast to existing research on network effects in

customer valuation, our network component can consequently be positive, negative, and zero, depending on the influence or susceptibility of the respective customer. Second and instead of a mere incorporation of direct network effects (Klier et al. 2014), we propose to incorporate also indirect influence in our network component. Thereby, our approach is inspired by the basic idea of prestige- and eigenvector-related centrality measures like Katz prestige (Katz 1953), Bonacich centrality (Bonacich 1972), or the PageRank algorithm introduced by Brin and Page (1998). In contrast to other centrality measures, like degree centrality (cf. Freeman 1979), these measures are able to consider direct and indirect influence in networks. Indeed, PageRank is probably the most well-known algorithm to rank a web page's importance in the World Wide Web (WWW) based on the links pointing to this web page. In particular, the greater the amount of links a web page receives and the higher their importance, the greater is the importance of a web page itself (Brin and Page 1998; Page et al. 1999). By "iterating the computation until it converges" (Page et al. 1999, p. 4), the algorithm allows for a full network approach considering the entire network structure. Since our approach aims at accomplishing the latter for customer valuation such an iterative approach considering the customers' influence among all degrees of separation seems particularly promising to determine Δ network contribution. Note that, while our work is inspired by the iterative idea of prestige- and eigenvector-related centrality measures, it is not possible to directly use or simply adapt these measures for our purpose. With respect to the PageRank algorithm, for example, there is a significant difference to our context since we do not increase a node's value based on the edges pointing to it but based on the edges pointing away from it. This is due to the fact that in our case a customer's value is higher the more customer s/he influences (i.e., edges pointing from him/her to other customers). Considering the mirror-inverted effect, a node's value is decreased based on the edges pointing to it.

Basic Model of the Customer Lifetime Network Value

Along the lines of the classic CLV (Berger and Nasr 1998), we define the CLNV as the present value (discount rate: $d \in \mathbb{R}^+$) of a customer's assigned current and expected future cash flows with respect to the expected lifetime $T \in \mathbb{N}$ of the customer relationship.¹ Thereby, building on previous works (Domingos and Richardson 2001; Weinberg and Berger 2011), we define the customer's assigned cash flows as the sum of the expected cash flows $CF_{i,t} \in \mathbb{R}$ generated by customer i in period t and a network component. Latter differs from existing research: First, instead of solely including the positive effect a customer has on the network (e.g., induced by referrals to others), we also consider the positive effect the network has on the customer (e.g., induced by referrals of others). Second, we take the entire network structure into account, thus incorporating also indirect influence among customers. Hence,

¹ An overview of the mathematical notation is provided in Table 6 (cf. Appendix 1).

the network component is determined by subtracting the cash flows $CF_{i,t}^{influenced} \in \mathbb{R}$ of customer i that are induced by direct and indirect positive influence of other customers from the cash flows $CF_{i,t}^{influence} \in \mathbb{R}$ of other customers that are induced by the direct and indirect positive influence of customer i . The CLNV of a customer i is defined as follows:

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

$CF_{i,t}^{influence}$ comprises all cash flows of other customers j in period t that have been induced directly or indirectly by customer i . The respective set of customers j being influenced directly by customer i in period t is referred to as $Influenced(i, t)$. Along the same lines, we define $Influence(j, t)$ as the set of customers exerting direct influence on customer j in period t . Referring to a customer $j \in Influenced(i, t)$, $CF_{i,t}^{influence}$ on the one hand comprises cash flows induced by the influence of customer i which are generated by customer j and are thus part of $CF_{j,t}$. On the other hand, $CF_{i,t}^{influence}$ must also take into account the indirect influence of customer i via customer j on other customers in the network. Therefore, we build our approach on the basic idea of prestige- and eigenvector-related centrality measures and add an iterative component $CF_{i,t}^{influence}$. By this means, a customer i 's influence among all degrees of separation is included in $CF_{i,t}^{influence}$. The share of a customer j 's cash flows $CF_{j,t}$ and $CF_{j,t}^{influence}$, which traces back to the influence of other customers in the network, is represented by the parameter $\alpha \in [0, 1]$.² The respective cash flows ($\alpha \cdot CF_{j,t}$ and $\alpha \cdot CF_{j,t}^{influence}$) are allocated to the customers exerting influence on customer j in period t . Thereby, to ensure a fair distribution of induced cash flows among all influencers, customer i is ascribed the share $\frac{s_t^{i \rightarrow j}}{\sum_{k \in Influence(j, t)} s_t^{k \rightarrow j}}$ depending on his/her relative strength of influence $s_t^{i \rightarrow j} \in \mathfrak{R}$ on customer j in period t with respect to the strength of influence $s_t^{k \rightarrow j}$ of all customers $k \in Influence(j, t)$ on customer j . For each degree of separation the influence and therefore the share of the cash flows tracing back to the influence of customer i is reduced by the factor $\alpha \in [0; 1[$. Therefore, a diminishing effect in α with $0 \leq \alpha < 1$ (i.e. $\alpha, \alpha^2, \alpha^3, \dots$ where $1 > \alpha > \alpha^2 > \alpha^3 > \dots > 0$ holds) can be observed. Due to this diminishing effect and in accordance with the convergence of the geometric series for parameters from the interval $[0; 1[$ the single summands approach zero and $CF_{i,t}^{influence}$ converges. Altogether $CF_{i,t}^{influence}$ can be expressed as denoted in Equation (2).

² It is generally possible to define the share of cash flows tracing back to influence in the network as a customer and/or period specific parameter. To do so, the parameter α may for example be replaced by the parameter $\alpha_t^j \in [0, 1]$ representing the share of customer j 's cash flows in period t , which traces back to the influence of other customers in the network. By means of the parameter α_t^j it can be considered that some customers in the network may be more susceptible to social influence than others and that this fact may vary over time. For reasons of simplicity, we refrain from this differentiation at this point.

$$CF_{i,t}^{influence} = \sum_{j \in Influenced(i,t)} \frac{s_t^{i \rightarrow j}}{\sum_{k \in Influence(j,t)} s_t^{k \rightarrow j}} (\alpha \cdot CF_{j,t} + \alpha \cdot CF_{j,t}^{influence}) \quad (2)$$

Along the same lines, we define $CF_{i,t}^{influenced}$ as the sum of all cash flows of customer i in period t that are induced by the direct and indirect influence of other customers. Thereby, both the cash flows generated by customer i ($CF_{i,t}$) and the cash flows induced by the direct or indirect influence of customer i ($CF_{i,t}^{influence}$) have to be considered accordingly. Thus,

$CF_{i,t}^{influenced}$ is defined as stated in Equation (3) (with $\sum_{j \in Influence(i,t)} \frac{s_t^{j \rightarrow i}}{\sum_{k \in Influence(i,t)} s_t^{k \rightarrow i}} = 1$):

$$CF_{i,t}^{influenced} = \sum_{j \in Influence(i,t)} \frac{s_t^{j \rightarrow i}}{\sum_{k \in Influence(i,t)} s_t^{k \rightarrow i}} (\alpha \cdot CF_{i,t} + \alpha \cdot CF_{i,t}^{influence}) = \alpha \cdot CF_{i,t} + \alpha \cdot CF_{i,t}^{influence} \quad (3)$$

Finally, based on Equations (1) to (3) we define the CLNV of a customer i as follows:

$$CLNV_i = \sum_{t=0}^T \frac{CF_{i,t} + \sum_{j \in Influenced(i,t)} \frac{s_t^{i \rightarrow j}}{\sum_{k \in Influence(j,t)} s_t^{k \rightarrow j}} (\alpha \cdot CF_{j,t} + \alpha \cdot CF_{j,t}^{influence}) - (\alpha \cdot CF_{i,t} + \alpha \cdot CF_{i,t}^{influence})}{(1+d)^t} \quad (4)$$

Extension of the Basic Model considering Negative Social Influence

In the basic model of the CLNV as introduced above we focused on positive social influence and did not include the effect of possible negative WOM (Kumar et al. 2010a; Weinberg and Berger 2011). Nevertheless, it is important to keep in mind that negative influence among customers may indeed result in cash flow potential of customers that cannot be realized ("economic damage"). To address this issue, in this subsection, based on Equation (1) of the basic model of the CLNV, we propose an extension subtracting an additional value component to account for the effect of possible negative social influence:

$$CLNV_i = \sum_{t=0}^T \frac{CF_{i,t} + (CF_{i,t}^{influence} - CF_{i,t}^{influenced}) - (CF_{i,t}^{negative_influence} - CF_{i,t}^{negatively_influenced})}{(1+d)^t} \quad (5)$$

$CF_{i,t}^{negative_influence}$ comprises the additional cash flow potential of other customers that cannot be realized in period t due to direct or indirect negative influence of customer i . $CF_{i,t}^{negatively_influenced}$ denotes the additional cash flow potential of customer i that cannot be realized in period t due to negative influence of other customers on customer i . Analogously to the term $(CF_{i,t}^{influence} - CF_{i,t}^{influenced})$ representing the network effects attributable to positive influence in the basic model of the CLNV, the network effects resulting from negative influence are considered in an additional network component $(CF_{i,t}^{negative_influence} - CF_{i,t}^{negatively_influenced})$ which is subtracted in the extended model (cf. Equation (5)). By this means, positive and negative influence are considered in a well-founded way not mixing up the respective effects. Thereby, $CF_{i,t}^{negative_influence}$ and $CF_{i,t}^{negatively_influenced}$ can be defined along the lines of the respective parameters of the basic model incorporating direct and

indirect network effects (cf. Equations (2) and (3)), however, not referring to positive influence and cash flows induced by positive influence in period t but to negative influence and additional cash flow potential of customers that cannot be realized in period t due to negative influence.

Illustrative Example

Basic Model of the Customer Lifetime Network Value

Consider Figure 2 for a sample customer network to illustrate the application of the CLNV. In this example we supplemented the network previously introduced by further information on cash flows, $CF_{i,t}$, and the strength of positive influence, $s_t^{i \rightarrow j}$. A time horizon of one period ($T = 1$), a discount rate of 10% ($d = 0.10$), and a share of cash flows tracing back to influence in the network of 50% ($\alpha = 0.50$) are assumed

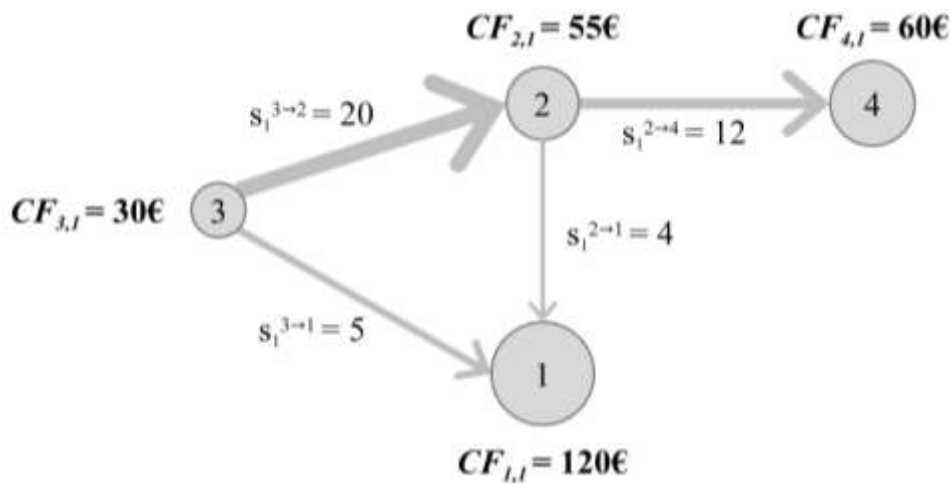


Fig 2 Sample Customer Network

First, $CF_{i,t}^{influence}$ is calculated using Equation 2. In most real-world cases, manually calculating $CF_{i,t}^{influence}$ for all nodes might be difficult due to its iterative component (to see how to cope with this issue cf. subsection “Application of the Customer Lifetime Network Value”). However, in our example, with customers 1 and customer 4 not exerting any influence resulting in $CF_{1,1}^{influence} = CF_{4,1}^{influence} = 0€$, a manual calculation is possible and for illustration purposes advantageous. The cash flows induced by customer 2 can be calculated as follows: $CF_{2,1}^{influence} = 4/9 \cdot (0.50 \cdot 120€ + 0.50 \cdot 0€) + 12/12 \cdot (0.50 \cdot 60€ + 0.50 \cdot 0€) = 56.67€$. In this respect, $4/9$ represents the relative strength of influence customer 2 exerts on customer 1, calculated by comparing the absolute strength of influence of customer 2 on customer 1 ($s_1^{2 \rightarrow 1} = 4$) to the overall strength of influence that customer 1 receives from the network (i.e., $s_1^{2 \rightarrow 1} + s_1^{3 \rightarrow 1} = 9$). The factor $12/12$ is calculated analogously. On this basis, $CF_{3,1}^{influence}$ can be determined to

$CF_{3,1}^{influence} = 5/9 \cdot (0.50 \cdot 120\text{€} + 0.50 \cdot 0\text{€}) + 20/20 \cdot (0.50 \cdot 55\text{€} + 0.50 \cdot 56.67\text{€}) = 89.17\text{€}$. Second, $CF_{i,t}^{influenced}$ is calculated for each customer applying Equation 3. For example, $CF_{3,1}^{influenced}$ yields 0€, as customer 3 is not influenced by any other customer. For customer 2, however, $CF_{2,1}^{influenced}$ is calculated as follows: $CF_{2,1}^{influenced} = 20/20 \cdot (0.50 \cdot 55\text{€} + 0.50 \cdot 56.67\text{€}) = 55.84\text{€}$. Finally, the CLNV can be calculated using Equation 4. For customer 3, this results in $CLNV_3 = (30\text{€} + 89.17\text{€} - 0\text{€}) / (1 + 0.10)^1 = 119.17\text{€} / 1.10^1 = 108.34\text{€}$. Table 1 summarizes the results. Customer 1 and customer 4 have a negative net contribution to the network ($CF_{i,1}^{influence} - CF_{i,1}^{influenced}$), while customer 3 has a highly positive one and customer 2's is close to zero.

Table 1 CLNV Example (basic model)

	Customer 1	Customer 2	Customer 3	Customer 4
Individual cash flows $CF_{i,1}$ [€] (present value [€] / CLV_i)	120.00 (109.09)	55.00 (50.00)	30.00 (27.27)	60.00 (54.54)
Δ network contribution [€] (present value [€])	-60.00 (-54.55)	0.83 (0.75)	89.17 (81.07)	-30.00 (-27.27)
$CF_{i,1}^{influence}$ [€] (present value [€])	0.00 (0.00)	56.67 (51.51)	89.17 (81.07)	0.00 (0.00)
$CF_{i,1}^{influenced}$ [€] (present value [€])	60.00 (54.55)	55.84 (50.76)	0.00 (0.00)	30.00 (27.27)
$CLNV_i$ [€]	54.54	50.75	108.34	27.27

To illustrate the impact of network effects in customer valuation, we compare the CLNV of all customers with the classic CLV of 109.09€ for customer 1, 50.00€ for customer 2, 27.27€ for customer 3, and 54.54€ for customer 4 (cf. present value of individual cash flows in Table 1). While customer 3 is not influenced by other customers, customer 1 and customer 4 "owe" a share of their cash flows to the network. As a consequence, their CLNV is substantially lower than their classic CLV. In contrast, the CLNV for customer 3 is considerably higher than the classic CLV, since s/he is inducing a share of the cash flows of the customers 1, 2, and 4. 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 roughly equal the cash flows that customer 2 "owes" to the network due to the influence of customer 3. This reflects the basic idea of our model reallocating cash flows without changing the overall value of the network. The sum over the $CLNV_i$ and the CLV_i for all four customers both yield 240.90€.

To illustrate the impact of indirect network effects, we investigate the customers' values when neglecting the iterative component of Equation 2. The value of customer 3, for instance, is underestimated by about 25€ (24%) when solely focusing on direct influence. Since customer 2 is the intermediary of customer 3's indirect influence on the network, the value of customer 2 is consequently overestimated by about 25€ (50%) when neglecting indirect influence. For the customers 1 and 4 no differences are observed. This is due to the fact that they neither are intermediaries nor exert indirect influence inside the network. Thus, this example illustrates the importance of incorporating not only direct but also indirect network effects in customer valuation.

Extension of the Basic Model considering Negative Social Influence

Considering negative social influence can be illustrated in a similar manner. Indeed, the underlying idea of the model's extension is to reallocate additional cash flow potential of customers that cannot be realized due to negative influence considering direct and indirect network effects following the iterative idea already pursued to account for positive influence in the basic model (cf. Equations (2) and (3)). Thereby, considering the respective additional cash flow potential of customers that cannot be realized due to negative influence once for the customers negatively influenced (cf. $CF_{i,t}^{influenced}$) and once for the customers exerting negative influence (cf. $CF_{i,t}^{influence}$) with different signs (cf. Equations (5)) ensures that the overall value of the network does not change compared to the basic model ("zero-sum logic" of the model extension).

To illustrate the basic idea of the extension of the basic model, we slightly supplement the example introduced before (cf. Figure 2) as follows: Customer 4 exerts direct negative influence on customer 1. The additional cash flow potential of customer 1 that cannot be realized due to this negative influence is 20€ (i.e. $CF_{1,1}^{negatively_influenced} = 20€$). As we do not observe negative influence between any other pair of customers, it follows that $(CF_{1,1}^{negative_influence} - CF_{1,1}^{negatively_influenced}) = (0€ - 20€) = -20€$ for customer 1, $(CF_{4,1}^{negative_influence} - CF_{4,1}^{negatively_influenced}) = (20€ - 0€) = 20€$ for customer 4, and accordingly 0€ for all other customers i with $i \in \{2,3\}$. Incorporating the additional value component to account for the effect of negative influence in the CLNV using Equation (5) leads to $CLNV_1 = (120€ + (0€ - 60€) - (0€ - 20€))/(1 + 0.10)^1 = 80€/1.10^1 = 72.73€$ for customer 1 and $CLNV_4 = (60€ + (0€ - 30€) - (20€ - 0€))/(1 + 0.10)^1 = 10€/1.10^1 = 9.09€$ for customer 4, respectively. Table 2 summarizes the results for the extended model of the CLNV.

Table 2 CLNV Example (extension of the basic model)

	Customer 1	Customer 2	Customer 3	Customer 4
Individual cash flows $CF_{i,1}$ [€] (present value [€] / CLV_i)	120.00 (109.09)	55.00 (50.00)	30.00 (27.27)	60.00 (54.54)
Positive influence (basic model)				
Δ network contribution (positive influence) [€] (present value [€])	-60.00 (-54.55)	0.84 (0.75)	89.17 (81.07)	-30.00 (-27.27)
Negative influence (extension)				
Δ network contribution (negative influence) [€] (present value [€])	-20.00 (-18.18)	0.00 (0.00)	0.00 (0.00)	20.00 (18.18)
$CF_{i,1}^{negative_influence}$ [€] (present value [€])	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	20.00 (18.18)
$CF_{i,1}^{negatively_influenced}$ [€] (present value [€])	20.00 (18.18)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
$CLNV_i$ [€]	72.72	50.75	108.34	9.09

Compared to the results of the basic model of the CLNV, on the one hand, the higher CLNV for customer 1 **adequately reflects the customer's additional cash flow potential** – indeed, without the negative influence of customer 4, s/he would generate additional cash flows of 20€. On the other hand, the lower value for $CLNV_4$ represents that due to the negative influence of customer 4 20€ of the additional cash flow potential of customer 1 cannot be realized. Hence, the differences in value of both customers are taken into account and at the same time the sum of the customers' CLNVs (i.e. $CLNV_1 + CLNV_2 + CLNV_3 + CLNV_4 = 240.90$ €) stays the same and still equals the net present value of all cash flows generated by the whole customer base. The latter is important to ensure a consistent customer valuation neither disregarding nor double counting cash flows.

Demonstration of the Applicability

In the following, as an essential part of the Design Science research process (Gregor and Hevner 2013; Hevner et al. 2004; Peffers et al. 2007), we demonstrate the practical applicability of our CLNV model.

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 sportsmen interested in socializing and communicating about sports related topics like fitness, nutrition, or health. For instance, users discuss sports events like the soccer world cup 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 OSNs. One major difference to OSNs such as Facebook is, however, that the OSN did not have a public "wall" at the time

of our investigation. The public discussion forums of the OSN under consideration, enabling publicly visible one-to-many distribution of messages, were only rarely used. Rather, the users usually took the opportunity to send private messages to one specific other user within the OSN. Therefore, in the following we focus on this kind of messages. Here, the OSN under investigation provided in form of a private message functionality the possibility for users to establish direct and private one-to-one connections to other users. In 2009, the OSN's operators 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. During the time frame under consideration, the shop offered selected sports products with attractive discounts exclusively to members of the OSN.

In order to successfully launch and advertise the affiliated shop, the OSN's operators planned to run user specific targeted marketing campaigns. To do so, key users were supposed to be identified, segmented, and addressed based on their customer values. The operators emphasized that besides actual customers purchasing products, users who are actively involved in the OSN and recommend products to other users are 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 direct and indirect influence on other users' purchase decisions**. Hence, the classic CLV was not adequate for the required customer valuation. Instead we agreed to consider both direct and indirect network effects by using our CLNV model. Indeed, the OSN and its affiliated shop provide 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 gives us the rare opportunity to integrate network effects based on influence among (potential) customers into customer valuation. Please note that the focus of the application is on the revenues from the affiliated online shop only, we do not consider revenues from additional sources such as advertising.

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 3 for a description of the datasets. The first dataset comprises all users of the OSN and the 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, 264,017 messages were sent by 5,902 of these users in the period under investigation. The low share of users sending messages is typical for networks such as OSNs and has also been found in prior research (Benevenuto et al. 2009; Wilson et al. 2009). All of the 60,029 users received at least one message. 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. The minimum amount of purchases of these users was one, the maximum was eight.

The average gross contribution of a customer's purchase was 49.45€, with a maximum of 390€.

Table 3 Description of the Datasets (n = 60,029 Users)

Incidence	Totals	Respective users (% of all users)	Mean per respective user
Messages (sent)	264,017	5,902 (9.8%)	44.73
Messages (received)	264,017	60,029 (100.0%)	4.40
Purchases	650	497 (0.8%)	1.31
Gross contribution	24,577.92€	497 (0.8%)	49.45€

Application of the Customer Lifetime Network Value

At first, to apply the CLNV 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 OSN's operators. When determining the parameters of the model for our application and for illustration purposes we used simplifying assumptions where possible to reduce the complexity and not to distract readers from the proposed model constituting the core of this work. Moreover, we focused on the basic model of the CLNV. On the one hand, due to the fact that the shop was just in its ramp up phase, attracting new customers by leveraging effects of direct and indirect positive social influence (e.g., recommendation of new products and offers to other users of the OSN) seemed particularly important. On the other hand, the granularity and accuracy of the results of the basic model met the requirements of the OSN under consideration.

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 OSNs and enable a differentiated view on changes in user behavior. This is consistent with previous research (Kumar et al. 2007). In addition, monthly time periods acknowledge the fact that the affiliated shop had just been launched and therefore 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 (Helsen and Schmittlein 1993; Jain and Vilcassim 1991). Drawing on historic data, we were able to determine the lifetime of each customer relationship based on his/her historic transaction data.

Determination of the discount rate d . Discount rates strongly depend on the specific situation and the risks of a company. Therefore, we based our estimation on discussions

with the OSN's operators 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's operators 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 (Libai et al. 2013; Weinberg and Berger 2011).

Determination of the cash flows $CF_{i,t}$. The concept of the CLV and also the CLNV are forward looking and require a prediction of future cash flows. For our demonstration of the CLNV, we used historic transaction data as proxy drawing on existing approaches. **Analyzing the customers' historic purchasing behavior, we determined the cash flows generated by user i in period t ($CF_{i,t}$).** While previous research has in fact found historic data on revenues and costs to be good predictors for future revenues and costs (Kumar, Petersen et al. 2010), there are also studies raising the question whether historic behavior is a very accurate predictor for prospective behavior (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 demonstrate its applicability, we chose a simple backward looking perspective using historic data.** For future research and application 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 (Jain and Singh 2002; Singh and Jain 2013).

Determination of the share of cash flows tracing back to influence in the network α . The parameter α represents the share of a customer's cash flows which traces back to the influence of other people in the network. Where necessary, this parameter may also be determined on a customer and/or period specific basis.¹ Thereby, a parameter of $\alpha = 0$ implies that a company assesses no share of cash flows to be induced by influence at all. For instance, companies assuming that customers purchase their products independently of each other not being exposed to social influence at all would choose a parameter of 0. In that case, the results of the CLNV would coincide with the classic CLV. In contrast, a value for α close to 1 implies that a company considers almost all of the generated cash flows to be induced by influence in the network. Thus, companies assuming that purchases primarily rely on social influence would choose such a high value for the parameter α . In practice, each company has to determine (e.g., based on analyses of historical data or expert estimations) what proportion of the cash flows is accredited to the influence of other users. In case of the OSN under investigation, we used – based on respective discussions with the operators of the OSN – the value $\alpha = 0.5$ to reflect that the OSN assessed half of the cash flows generated by customers in the network to be induced by the influence of others. Unfortunately, due to the fact that the affiliated shop was just in its ramp up phase we could not draw on historical data to verify this choice by means of respective data analyses.

Determination of the strength of direct influence $s_t^{i \rightarrow j}$. Literature widely agrees upon the fact that the impact of social influence in OSNs strongly depends on the strength of the connections among users, which can be determined by the number of social interactions such as messages (Cheung and Lee 2010; Heidemann et al. 2010; Hinz et al. 2011; Kane et al. 2014; Kiss and Bichler 2008). In our application, in order to determine the strength of a **user i 's direct influence on user j ($st_i \rightarrow j$)**, we focused on the number of potentially purchase relevant private messages sent from user i to user j . Conversely, the strength of influence other users j have on him/her was estimated using the number of potentially purchase relevant private messages s/he received ($st_j \rightarrow i$). Thereby, analyzing the chronology of purchases and messages on a daily basis, each message within a time frame of 10 days before a purchase in period t was considered as potentially relevant for this purchase. For a better comparison of the influence of different time frames, the results for the time frames of 5 and 7 days can be found in the appendix (cf. Appendix 2). We considered therefore the fast-moving nature of online interactions and focused on private messages as the primary means of communication within the OSN. Being aware that correlation does not imply causation, the fact that we indeed observed a positive correlation (p -value < 0.01) between the number of messages and purchases may, however, also support our operationalization of the strength of influence to a certain extent. Since in case of our sports OSN no other relevant interactions besides private messages were observed, we considered no other forms of interaction. However, when significant interactions beside private messages occur and may influence **customers' purchase behavior in other contexts, these should be considered analogously**. For public discussion forums, for instance, the strength of influence can be determined based on the number of posts. Nonetheless, different forms of interactions have to be assessed regarding their influence potential. For example, a post in a public discussion forum may reach various recipients; however, the strength of influence of such a public post on a single recipient may significantly differ from the strength of influence of a private message personally addressing him/her. We also want to point out that regarding the quantification of the strength of influence $st_i \rightarrow j$ between users there may be other relevant aspects beside the mere number of messages sent within a certain time frame like user characteristics, personality, degree of connectivity, or the content of the conversation (Kumar et al. 2010a; Nitzan and Libai 2011; Wang et al. 2014).

Calculation of the CLNV. . Finally, we calculated the CLNV for each user. Analogous to prestige- and eigenvector-related centrality measures the CLNVs can be determined solving the respective system of equations containing one equation per customer i in the network (cf. Equation (4)) via eigenvector analysis. To do so, we used the power iteration method (cf. e.g., Golub and van Loan 2012) in the software package "NetworkX" for the exploration

and analysis of networks and network algorithms (Hagberg et al. 2008).³ The power iteration method can be used for calculating the eigenvector of sparse matrices and is known to converge fast (Lin and Cohen 2010). To ensure convergence of the power iteration method the iteration stops when the difference between the computed vectors is smaller than an error tolerance (error tolerance is defined as the *number of nodes in the graph* $\times 1.0^{-15}$) or alternatively after a maximum of 100 iterations. This configuration of the algorithm turned out to be sufficient for an adequate approximation. Using our software implementation, the CLNV was calculated for all 60,029 users. For the 1,978 users with a positive CLNV⁴, Table 4 provides an overview of the results considering the CLNV as well as its main components. On average, the *present value of individual cash flows* accounts for 11.95€. Due to the design of our model, the two opposing components, $CF_{i,t}^{influence}$ and $CF_{i,t}^{influenced}$, balance each other leading to an average *present value of Δ network contribution* of 0€. However, *the present value of Δ network contribution* varies substantially between -86.98€ (-50% of the particular user's present value of the generated cash flows) and 372.62€ (+500% of the particular user's present value of the generated cash flows). Most of the divergence results from the variance of users influencing other users ($CF_{i,t}^{influence}$). Taking all components together, the average $CLNV_i$ accounts for 11.95€, with a minimum of 0.01€ and a maximum of 447.16€. Thus, as designed in the model, the average CLNV coincides with the average *present value of individual cash flows*, since the CLNV reallocates cash flows but does not change the overall present value of the network of 23,633.50€. 1,978 users have a positive CLNV and therefore a positive value for the affiliated shop of the OSN. These are about 398% more users than the 497 customers that actually purchased products in the period under investigation

³ Vgl. <http://networkx.github.io/>

⁴ Results for the CLNV below 0.01€ were rounded to zero.

Table 4 Results of the Application (n = 1,978 Users)

	Mean	Minimum	Maximum	Standard deviation
Individual cash flows $CF_{i,1}$ [€] (present value [€] / CLV_i)	13.15 (11.95)	0.00 (0.00)	418.65 (380.59)	33.21 (30.19)
Δ network contribution [€] (present value [€])	0.00 (0.00)	-95.68 (-86.98)	409.88 (372.62)	14.99 (13.63)
$CF_{i,1}^{influence}$ [€] (present value [€])	3.01 (2.74)	0.00 (0.00)	901.76 (819.78)	27,59 (25.08)
$CF_{i,1}^{influenced}$ [€] (present value [€])	3.01 (2.74)	0.00 (0.00)	491.88 (447.16)	16.26 (14.78)
$CLNV_i$ [€]	11.95	0.01	447.16	30.27

Findings of the Application and Novel User Segmentation

For the discussion of the findings of the application, we compare the CLNV with the classic CLV and study the impact of direct and indirect network effects. In addition, based on the results, we propose a novel user segmentation. Note that in the following we refer to the 1,978 users with a positive CLNV.

Discussion of the Findings of the Customer Lifetime Network Value

The findings of the application of the CLNV are analyzed in three ways. First, we compare **the absolute values of the CLNV and the classic CLV. For both the overall sum is 23,633.50€.** The CLNV, however, alters the allocation of value among users compared to the classic CLV. In fact, we observe a significant difference (p-value < 0.001) between the CLNV and the classic CLV. Further, we observe on the one hand that for about 77.7% (1,536) of the users the CLV accounts for less than the CLNV. Thus, the value of these users would be underestimated when ignoring network effects and the OSN might spend insufficient resources on them. Moreover, due to a lack of purchases about 96.4% (1,481) of these underestimated users would even be completely ignored in marketing campaigns based on the classic CLV although being valuable for the OSN as their influence induces cash flows of other customers. On the other hand, for about 6.5% (128) the classic CLV accounts for more than the CLNV. When ignoring network effects, the OSN would overestimate the value of these users and might therefore spend too many resources on them.

Second, we compare the relative importance of users and ranked all 1,978 users once based on the CLNV and once based on the classic CLV. Depending on these rankings, we identified the top users (top 1%-users, top 10%-users, top 20%-users, top 30%-users) for each approach. Table 5 displays the number of users per top user group according to the CLNV and the number of users who are not included in the respective top user group when considering the classic CLV. For example, 30.0% of the top 1%-users regarding the CLNV are ranked

in a lower top user group regarding the classic CLV. Some of them are not even within the top 20%-users regarding the classic CLV. Hence, parts of the highly valuable users according to the CLNV would be completely ignored and resources might be spent in a less efficient way when designing a top user marketing campaign based merely on the CLV. Taking a look at the top 20%-users regarding the CLNV, around 10.4% are not among the top 20%-users and around 17.1% are not even assigned to the top 30%-users regarding the CLV. In consequence, classic marketing campaigns might focus on the “wrong” users while neglecting more valuable ones.

Table 5 Comparison of Top User Groups for the CLNV and the CLV (n = 1,978 Users)

Top user group	Number of users per respective top user group regarding the CLNV	Number of users not included in the respective top user group regarding the CLV
Top 1%-users	20	6 (30.0%)
Top 10%-users	198	18 (9.1%)
Top 20%-users	396	41 (10.4%)
Top 30%-users	593	67 (11.3%)

Third, we analyze the impact of direct and indirect network effects. Indeed, we observe a significant difference (p -value < 0.001) between the CLNV including both direct and indirect network effects and the CLNV including only direct network effects (cf. Klier et al. 2014). In fact, for about 81.2% (1,607) of the users the value differs when neglecting the indirect network effects. Thus, most of the users would be misvalued when solely considering direct network effects. In terms of numbers, this misvaluation indeed plays a central role: We observe a major difference between the sums of network effects based on direct influence (2,820.65€) and both direct and indirect influence (5,425.59€). Hence, almost 48.0% of all induced cash flows can be traced back to indirect influence, illustrating the importance of considering indirect network effects in customer valuation.

Taken together, we argue that it is very important to include both direct and indirect network effects in customer valuation. Even with the rather exemplary dataset of the OSN’s affiliated shop during its ramp up phase, we observed significant differences between the CLNV and the CLV. Nevertheless, it has to be noted that on basis of the real-world example we can only demonstrate the practical applicability of our approach but do not prove that the CLNV really improves efficiency regarding the way how marketing resources are spent in practice. However, we are confident that our proposed model may help to establish and maintain valuable customer relationships for example by focusing on the actually important top user groups.

4.3.2 Novel User Segmentation Based on the CLNV

The operators of the OSN intended to use the CLNV to design targeted marketing campaigns and improve advertising for the affiliated shop. In order to support these efforts, we defined distinct CLNV-based user segments and derived selected marketing goals for each segment (Kumar et al. 2007). However, it is important to note that the exemplary user segmentation presented here is only one potential use case of the application of the CLNV besides many others like enabling a value-oriented customer relationship management where the “true” customer value is needed to support decision making (e.g., in the context of customer acquisition or customer retention).

Inspired by the CLNV as segmentation criteria we used the CLNV’s two main components (cf. summands in the formula in the subsection “Basic Idea”) *present value of individual cash flows* and *present value of Δ network contribution* (cf. Figure 3).

<i>Present value of individual cash flows</i>	HIGH	Influenced Champions 6.4% of all users Average CLNV = 37.24€	Classic Champions 16.9% of all users Average CLNV = 46.20€	Influencing Champions 1.3% of all users Average CLNV = 47.99€
	LOW	Influenced Misers 0.1% of all users Average CLNV = 4.67€	Classic Misers 10.6% of all users Average CLNV = 0.36€	Influencing Misers 64.7% of all users Average CLNV = 1.71€
		NEGATIVE	NULL	POSITIV
		<i>Present value of Δ network contribution</i>		

Fig. 3 CLNV-based User Segments (n = 1,978 Users)

The first criterion is subdivided into the two degrees *high* and *low*, split by the arithmetic mean (11.95€) of the *present value of individual cash flows*. User segments that score high on the criterion *present value of individual cash flows* are named *Champions* and the ones scoring low *Misers* (Kumar et al., 2007). The second criterion is subdivided into the three degrees *positive*, *zero*, and *negative* with respect to the *present value of Δ network contribution*. Depending on the score of the second criterion, we refer to the *Champions* as *Influencing Champions* (i.e., users with a positive *present value of Δ network contribution*), *Classic Champions* (i.e., users with zero *present value of Δ network contribution*), and *Influenced Champions* (i.e., users with a negative *present value of Δ network contribution*).

Analogously, we define the segments that score 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 the proposed user segmentation: First, the average CLNV varies substantially between the six segments, from **47.99€ (*Influencing Champions*) to 0.36€ (*Classic Misers*)**. Note that the low value of the latter, and of the *Misers* in general, can be explained by their average *present value of individual cash flows* being close to 0€. In contrast, the *Influencing Champions* both influence other customers and at the same time make purchases, thus classifying as the most valuable segment. Second, the distribution of users across the six segments varies considerably. About 66.0% (1,305) of the users are classified as *Influencing* users. Thereby, solely about 1.3% (25) of the users perform well on both criteria, thus are assigned to the segment of *Influencing Champions*. Most users, in fact almost 64.7% (1,280), are segmented as *Influencing Misers*. Thus, they rarely make purchases, but mainly induce other users' cash flows. Note that regarding their CLV most of these users would be classified as invaluable and completely ignored in marketing campaigns. In contrast to the huge amount of *Influencing* users, less than 6.5% (128) of all users are classified as *Influenced* users. In particular, 6.4% (127) are assigned to the segment of *Influenced Champions*, thus they make purchases that are mainly induced by the influence of others. Merely 0.1% (1) belongs to the segment of *Influenced Misers*. Hence, we observe a large group of users (*Influencing* users) influencing a substantial smaller group of customers (*Influenced* users). This is due to the shop being in its ramp up phase with a rather modest number of purchases. Finally, around 28.5% (545) of the users are classified as *Classic* users, thus show no network effects at all. Thereby, almost 16.9% (334) belong to the segment of *Classic Champions*, while around 10.6% (211) are assigned to the segment of *Classic Misers*. Taken together, we identify **substantial potential to improve the users' value** by moving all other segments to *Influencing Champions*. Thus, we propose to aim for (1) turning *Misers* into *Champions* and (2) moving users from *Classic* and *Influenced* to *Influencing* users. In particular, the OSN should focus on the large segment of *Influencing Misers* and move them towards *Influencing Champions*.

Based on this user segmentation, we proposed a strategic marketing campaign. Thereby, **we determined the reasonable investment for each segment by comparing the user's present CLNV with the intended CLNV**. For illustration, selected marketing efforts for each segment are briefly sketched in the following.⁵

⁵ Please note that, while the presented user segmentation seems suitable for a first hand classification of users in relation to other users, an in-depth analysis as well as a long-term application of the segmentation should also put a stronger focus on absolute values.

Influencing Misers. To increase the *present value of individual cash flows* of *Influencing Misers*, by this means turning them into *Influencing Champions*, these users should be encouraged to increase individual purchases. As an example: For products other users bought as result of their recommendation, discounts could be offered to them. Such discounts could be complemented by an e-mail thanking for **recommending the shop's product**.

Influenced Champions and Classic Champions. To turn *Classic* and *Influenced Champions* into *Influencing Champions*, these users should be encouraged to actively exert influence on others. This could be achieved, for instance, by sending an e-mail after each purchase of *Classic* or *Influenced Champions* offering monetary rewards for a successful recommendation. In addition, e-mails to *Influenced Champions* could refer to the positive experiences with recommendations they received themselves.

Influenced and Classic Misers. Moving *Influenced* and *Classic Misers* towards the segment of *Influencing champions* requires increasing their amount of both purchases and recommendations. Thus, such users could be targeted by combining the marketing actions described above, i.e., offering monetary incentives for both purchasing products and using **their influence to induce other users' purchases in the OSN's affiliated shop**.

5 Conclusion, Limitations and Further Research

5.1 Contribution to Research and Practice

We propose a novel customer valuation model 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/her through purchases and a network component reflecting the *present value of his/her net contribution to the network* considering the entire network structure. The practical applicability of the basic model of the CLNV was exemplary demonstrated using a real-world dataset of a European OSN focusing on sports. The proposed model aims at allowing companies to evaluate their **customers in the context of OSNs by enabling the assessment of the "true value" of a customer** considering his/her social influence on other members of the network. Overall, the 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 others and customers that are influenced, the CLNV ensures a correct individual valuation of all customers in two ways. On the one hand a customer's value is not limited to his/her individual purchases but increased when s/he induces cash flows of others by his/her influence. On the other hand, by decreasing the value of a customer if **his/her cash flows are induced by the influence of others**, the customer's value is assessed more adequately and is not overestimated as in the classic CLV (Adamic and Adar 2003;

Berger and Nasr 1998; Guetzkow 1951) and in previous models considering network aspects (Kumar et al. 2007; 2010a, b; Weinberg and Berger 2011). Keeping both effects in mind, in our application we observed significant differences between the CLNV and the CLV. Both effects have a practical influence on decision making and are crucial for operators as, for example, “[f]ailure to include these social effects could lead to misallocation of scarce marketing resources” (Hogan et al. 2003, p. 197): On the one hand, without the CLNV customers who increase profits of a company mainly by influencing others would be ignored in marketing campaigns. On the other hand, the CLNV helps companies to avoid marketing to unprofitable customers who fail to generate own or induce other customers’ cash flows.

Second, the CLNV allows an allocation of not only direct but also indirect influence. Since influence in networks spreads virally through the entire customer network, indirect influence has to be considered when valuating customers in networks. Therefore, inspired by prestige- and eigenvector-related centrality measures the CLNV includes an iterative component, enabling the incorporation of influence among all degrees of separation. Consequently, in contrast to most of the existing methods (Klier et al. 2014), the CLNV allows for a full network approach altering customer valuation substantially. In fact, in our demonstrative application we observed a significant impact of indirect effects on the value of customers, thereby underlining the practical relevance of our approach. Hence, the CLNV contributes to customer valuation in two ways: On the one hand, the CLNV avoids underestimating the value of customers who spread influence inside a network. On the other hand, the CLNV avoids overestimating the value of customers who are the intermediaries of the former. Hence, based on the results of the CLNV, a more effective spending of existing marketing budget can be achieved.

Third, the CLNV enables a sound determination of a company’s CE: Our model is the first to contain direct as well as indirect network effects and ensures at the same time a sound **determination of a company’s CE by aggregating individual customer values.** Key to this is our integrated network perspective ensuring that network effects are not double counted. Double counting is a serious issue since 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. Thereby, decision makers 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 customer decisions (e.g., acquisition of new customers or bounding of existing ones at too high costs).

Taken together, the CLNV provides a novel and accurate approach for customer valuation in context of network effects. Building on this, we exemplarily demonstrated a new and well-founded user segmentation based on the CLNV's two main components *present value of individual cash flows* and *present value of Δ network contribution*. This segmentation extends both the informative content of segmentation based on the classic CLV and the segmentation based on previous models considering network effects (not accounting for indirect effects and negative net network contributions). Thus, applied in practice, the segmentation based on the CLNV may help companies to design better marketing campaigns.

5.2 Limitations and Further Research

Our model is subject to limitations which – to a certain extent – also serve as promising starting points for future research. First, by means of the real-world case of the European OSN we could demonstrate the practical applicability of the basic model of the CLNV. However, we could not prove superiority of the new approach regarding improved efficiency with respect to the way how marketing resources are spent nor could we prove that the redistribution of the discounted cash flows as proposed by the model really reflects the **“true” impact on buying decisions in practice. Evaluating or proving this practical superiority** would require a field experiment. Unfortunately, with the OSN focusing on sports we were not able to conduct such an experiment. For future research we are in contact with two companies from the banking and insurance sector which are highly interested in an application of the CLNV model. We hope that we will be able to conduct such a field experiment to substantiate the practical evaluation of our approach including the extension of the basic model considering negative influence in the future.

Second, when determining the parameters of the basic model in our application and for illustration purposes we used simplifying assumptions where possible to reduce the complexity and to keep the focus on the proposed model. For example, we determined the strength of influence $st_{i \rightarrow j}$ between users based on the mere number of messages sent within a certain time frame. In doing so, like many prestige- and eigenvector-related centrality measures (e.g. classical PageRank algorithm) we disregard other relevant aspects like the content of the conversation which may be used to determine much more precisely the strength of influence $st_{i \rightarrow j}$ **or would help to determine a sort of “success rate” whether a certain purchase was actually triggered by a message of another user or not.** Without any doubt, the appropriate determination of the parameters of the model for the underlying context of application poses a major challenge regarding the practical applicability. To approach this issue, it seems particularly promising to make use of contributions in the emerging research strand of Social Media Analytics (Stieglitz et al. 2014). With the help of advanced text mining and sentiment analysis techniques (Gamon et al. 2005; Hu and Liu 2004;

Pang and Lee 2008), for example, content of user interactions may be distinguished between (particularly) relevant vs. non-relevant, positive vs. negative, etc. to further refine the results in the future.

Third, in the basic model and the practical application of our approach we focused on positive social influence and did not include the effect of potentially negative social influence, for example in form of negative WOM. To alleviate this issue to a certain extent, we proposed an extension of the basic model considering both positive and negative social influence. In this context, however, it has to be noted that the determination of the parameters of the extended model is even more challenging compared to the basic model. Indeed, it is **no longer sufficient to estimate individual customers' real cash flows but also the individual customers' imaginary cash flows that cannot be realized due to negative social influence** of other customers. Actually, the latter seem particularly difficult to grasp and may only be roughly estimated.

Fourth, OSNs are never "closed systems" and WOM outside electronic networks is of major importance as well (Berger 2014). Against this background, focusing on the online world when calculating the CLNV can only provide a limited view and may be insufficient in some cases. Therefore, we see the integrated quantification of both online and offline influence as a very promising topic for future research (Liu et al. 2012; Scarpi et al. 2014). This seems particularly challenging due to the fact that for the context of OSNs it is much easier to determine and estimate the customer specific parameters of the CLNV in an automated way (Tang and Guo 2015) (e.g., based on messages exchanged electronically and using text mining and sentiment analysis techniques and algorithms).

Finally, we focused on social influence on present customers assuming the customer network to be stable. Including growth of customer networks into valuation could be another interesting journey for further research.

We hope that our paper contributes to a better understanding of customer valuation in the context of network effects and stimulates further research in this exciting field.

Appendix 1

Table 6 Overview of the mathematical notations

Mathematical notation	Description
$CF_{i,t} \in \mathfrak{R}$	Cash flows generated individually by customer i in period t .
$CF_{i,t}^{influence} \in \mathfrak{R}$	Cash flows of customers induced by the direct and indirect positive influence of customer i in period t .
$CF_{i,t}^{influenced} \in \mathfrak{R}$	Cash flows of customer i induced by the direct and indirect positive influence of other customers in period t .
$CF_{i,t}^{negative_influence}$	Cash flow potential of other customers that cannot be realized in period t due to direct or indirect negative influence of customer i .
$CF_{i,t}^{negatively_influenced}$	Cash flow potential of customer i that cannot be realized in period t due to negative influence of other customers on customer i .
$Influenced(i, t)$	Set of customers directly influenced by customer i in period t .
$Influence(j, t)$	Set of customers exerting direct influence on customer j in period t .
$T \in \mathbb{N}$	Expected lifetime of the customer relationship.
$d \in \mathfrak{R}^+$	Discount rate.
$s_t^{i \rightarrow j} \in \mathfrak{R}$	Strength of direct influence exerted by customer i on customer j in period t .
$\alpha \in [0, 1[$	Share of cash flows tracing back to influence in the network.

Appendix 2

We additionally carried out the calculation of the CLNV for the time frame of 5 days (cf. Table 7, 8, Figure 4) and the time frame of 7 days (cf. Table 9, 10, Figure 5).

Table 7 Results of the Application (time frame = 5 days, n = 1,287 Users)

	Mean	Minimum	Maximum	Standard deviation
Individual cash flows $CF_{i,1}$ [€] (present value [€] / CLV_i)	21.66 (19.69)	0.00 (0.00)	418.65 (380.59)	40.42 (36.74)
Δ network contribution [€] (present value [€])	0.00 (0.00)	-65.30 (-59.37)	285.79 (259.81)	12.74 (11.58)
$CF_{i,1}^{influence}$ [€] (present value [€])	3.21 (2.92)	0.00 (0.00)	571.57 (519.61)	22.30 (20.27)
$CF_{i,1}^{influenced}$ [€] (present value [€])	3.21 (2.92)	0.00 (0.00)	285.79 (259.81)	13.71 (12.46)
$CLNV_i$ [€]	19.69	0.01	380.59	35.98

Table 8 Comparison of Top User Groups for the CLNV and the CLV (time frame = 5 days, n = 1,287 Users)

Top user group	Number of users per respective top user group regarding the CLNV	Number of users not included in the respective top user group regarding the CLV
Top 1%-users	12	2 (16.7%)
Top 10%-users	120	16 (13.3%)
Top 20%-users	240	20 (8.3%)
Top 30%-users	360	26 (7.2%)

Present value of individual cash flows	HIGH	Influenced Champions 6.6% of all users Average CLNV = 41.50€	Classic Champions 25.1% of all users Average CLNV = 52.80€	Influencing Champions 1.6% of all users Average CLNV = 49.00€
	LOW	Influenced Misers 1.0% of all users Average CLNV = 8.01€	Classic Misers 11.1% of all users Average CLNV = 6.22€	Influencing Misers 54.6% of all users Average CLNV = 2.57€
		NEGATIVE	NULL	POSITIV
		<i>Present value of Δ network contribution</i>		

Fig. 4 CLNV-based User Segments (time frame = 5 days, n = 1,287 Users)

Table 9 Results of the Application (time frame = 7 days, n = 1,470 Users)

	Mean	Minimum	Maximum	Standard deviation
Individual cash flows $CF_{i,1}$ [€] (present value [€] / CLV_i)	12.76 (11.60)	0.00 (0.00)	340.88 (309.44)	28.28 (25.71)
Δ network contribution [€] (present value [€])	0.00 (0.00)	-51.29 (-46.62)	216.16 (196.51)	9.81 (8.92)
$CF_{i,1}^{influence}$ [€] (present value [€])	2.31 (2.10)	0.00 (0.00)	432.32 (393.02)	17.43 (15.85)
$CF_{i,1}^{influenced}$ [€] (present value [€])	2.31 (2.10)	0.00 (0.00)	216.16 (196.92)	9.15 (9.75)
$CLNV_i$ [€]	(11.60)	(0.01)	(309.44)	(25.29)

Table 10 Comparison of Top User Groups for the CLNV and the CLV (time frame = 7 days, n = 1,470 Users)

Top user group	Number of users per respective top user group regarding the CLNV	Number of users not included in the respective top user group regarding the CLV
Top 1%-users	15	4 (26.7%)
Top 10%-users	147	17 (11.6%)
Top 20%-users	294	29 (9.9%)
Top 30%-users	441	21 (4.8%)

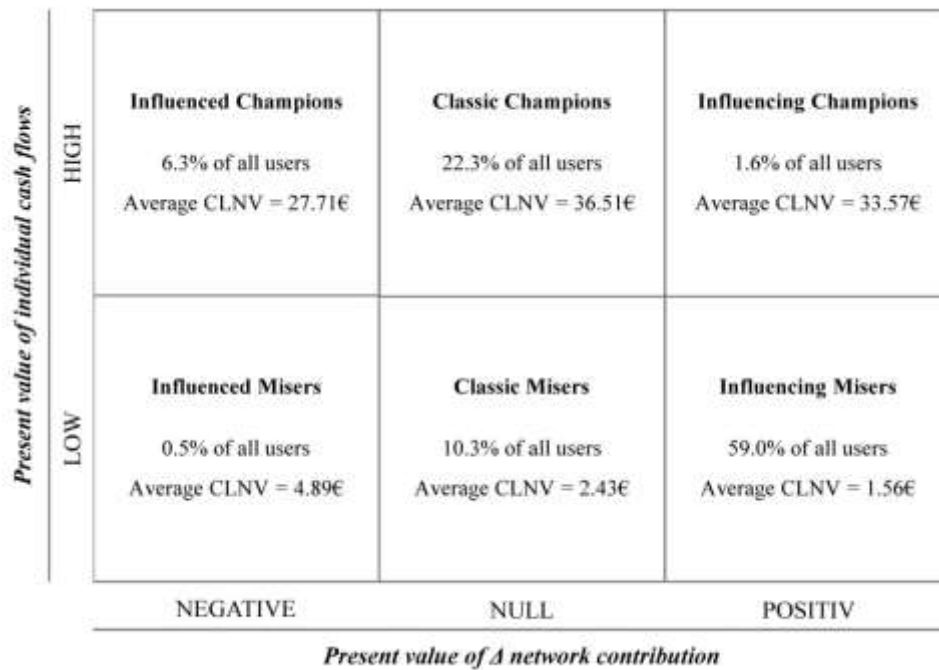


Fig. 5 CLNV-based User Segments (time frame = 7 days, n = 1,470 Users)

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

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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

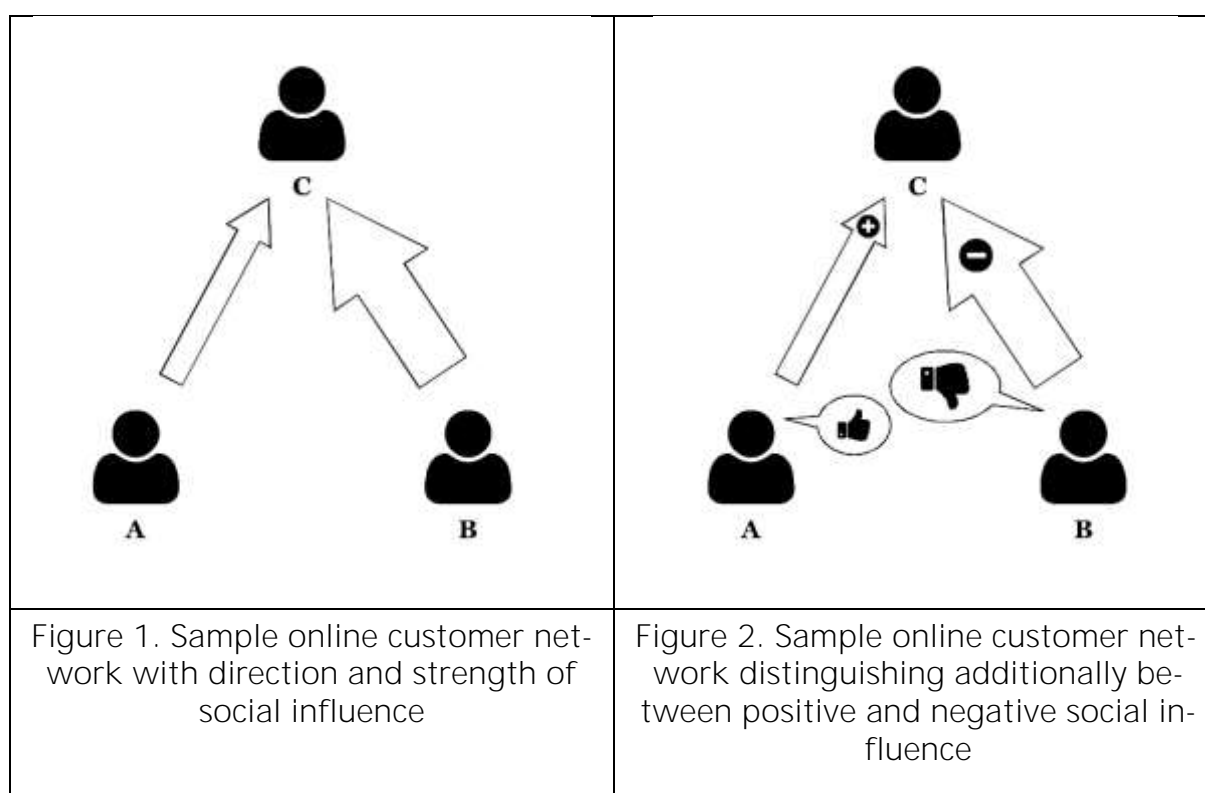
frequently engage in conversations with other customers. On the one hand, these studies **uncover social influence's significant monetary power through its impact on customers' purchase decisions**. On the other hand, they uncover the importance for companies to measure and account for **customers' social 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.



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 $s_{positive}^{i \rightarrow j}$. 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 $\frac{s_{positive}^{i \rightarrow j}}{\sum_{k \in \text{positive influence}(j)} s_{positive}^{k \rightarrow j}}$, where $\sum_{k \in \text{positive influence}(j)} s_{positive}^{k \rightarrow j}$ 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 $vc_i^{\text{positive influence}}$ for customer i due to his/her positive influence on other customers in an online customer network as follows:

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

where $\text{positively influenced}(i)$ is the set of customers directly positively influenced by customer i ,

$s_{\text{positive}}^{i \rightarrow j} \in \mathfrak{R}$ the strength of direct positive social influence exerted by customer i on customer j ,

$\text{positive influence}(j)$ 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,

$vc_j \in \mathfrak{R}$ the value contribution generated individually by customer j , and

$vc_j^{\text{positive influence}} \in \mathfrak{R}$ the value contribution due to direct and indirect positive social influence exerted by customer j .

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

$$vc_i^{\text{positively influenced}} = \sum_{j \in \text{positive influence}(i)} \frac{s_{\text{positive}}^{j \rightarrow i}}{\sum_{k \in \text{positive influence}(i)} s_{\text{positive}}^{k \rightarrow i}} (\alpha \cdot vc_i + \alpha \cdot vc_i^{\text{positive influence}}), \quad (2)$$

where	$positive\ influence(i)$	is the set of customers inducing direct positive social influence on customer i ,
	$s_{positive}^{j \rightarrow i} \in \mathfrak{R}$	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,
	$vc_i \in \mathfrak{R}$	the value contribution generated individually by customer i , and
	$vc_i^{positive\ influence} \in \mathfrak{R}$	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 $s_{negative}^{i \rightarrow j}$, 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 $\frac{s_{negative}^{i \rightarrow j}}{\sum_{k \in \text{negative influence}(j)} s_{negative}^{k \rightarrow j}}$.

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 j '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:

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

where *negatively influenced*(i) is the set of customers directly negatively influenced by customer i ,

$s_{negative}^{i \rightarrow j} \in \mathfrak{R}$	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,
$lvc_j \in \mathfrak{R}$	the lost value contribution of customer j due to negative social influence of other customers in the network, and
$lvc_j^{negative\ influence} \in \mathfrak{R}$	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:

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

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

$s_{negative}^{j \rightarrow i} \in \mathfrak{R}$	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,
$lvc_i \in \mathfrak{R}$	the lost value contribution of customer j due to negative social influence of other customers in the network, and
$lvc_i^{negative\ influence} \in \mathfrak{R}$	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:

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

- where $vc_i \in \mathfrak{R}$ 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 $s_{positive}^{i \rightarrow j}$ or negative social influence $s_{negative}^{i \rightarrow j}$ 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., $s_{negative}^{i \rightarrow j} = 5$). 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 ($s_{positive}^{i \rightarrow j}$) or negative ($s_{negative}^{i \rightarrow j}$).

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*.

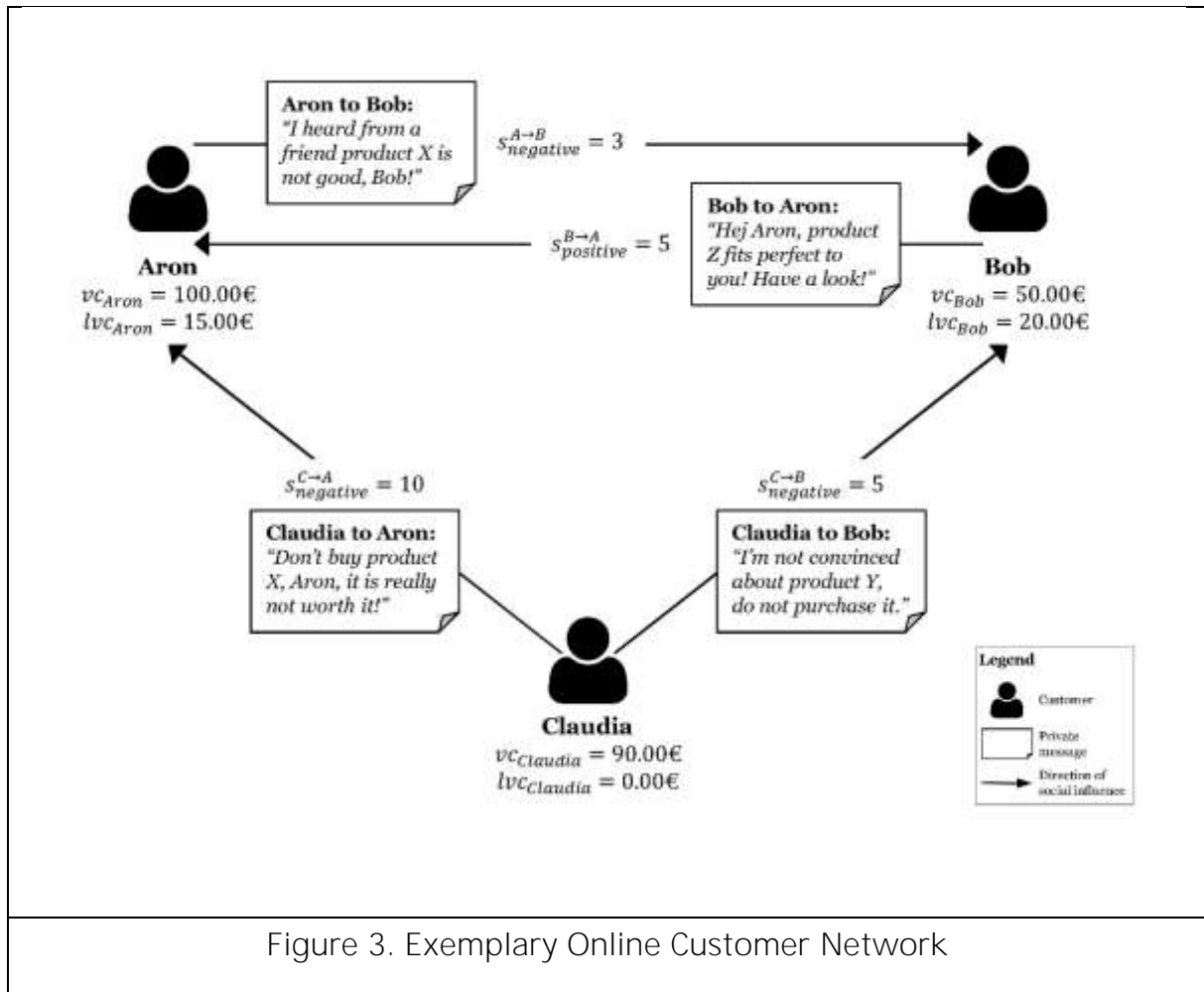


Figure 3. Exemplary Online Customer Network

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 ($s_{positive}^{B-A} = 5$). 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 ($s_{negative}^{C-A} = 10$) 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 ($s_{negative}^{C-B} = 5$) 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:

$$vc_{Bob}^{positive\ influence} = \frac{5}{5} * (0.5 * 100.00\text{€} + 0.5 * 0.00\text{€}) = 50.00\text{€} \text{ (cf. Equation 1). Second,}$$

we calculate the value contribution of *Aron* attributed to *Bob's* positive social influence:

$$vc_{Aron}^{positively\ influenced} = \frac{5}{5} * (0.5 * 100.00\text{€} + 0.5 * 0.00\text{€}) = 50.00\text{€} \text{ (cf. Equation 2).}$$

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:

$$lvc_{Aron}^{negative\ influence} = \frac{3}{8} * (20.00\text{€} + 0.7 * 0.00\text{€}) = 7.50\text{€} \text{ (cf. Equation 3).}$$

On the other hand, the lost value contribution due to *Claudia's* negative social influence on *Aron* and *Bob* is calculated: $lvc_{Claudia}^{negative\ influence} = \frac{10}{10} * (15.00\text{€} + 0.7 * 7.50\text{€}) + \frac{5}{8} * (20.00\text{€} + 0.7 * 0.00\text{€}) = 32.75\text{€}$ (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:

$$lvc_{Aron}^{negatively\ influenced} = \frac{10}{10} * (15.00\text{€} + 0.7 * 7.50\text{€}) = 20.25\text{€} \text{ and } lvc_{Bob}^{negatively\ influenced} = \frac{3}{8} * (20.00\text{€} + 0.7 * 0.00\text{€}) + \frac{5}{8} * (20.00\text{€} + 0.7 * 0.00\text{€}) = 20.00\text{€} \text{ (cf. Equation 4).}$$

Finally, the integrated value contribution ivc_i for each customer is calculated. *Aron's* integrated value contribution is therefore calculated as $ivc_{Aron} = 100.00\text{€} + (0.00\text{€} - 50.00\text{€}) + (20.25\text{€} - 7.50\text{€}) = 62.75\text{€}$ (cf. Equation 5). Accordingly, the integrated value contributions for *Bob* ($ivc_{Bob} = 50.00\text{€} + (50.00\text{€} - 0.00\text{€}) + (20.00\text{€} - 0.00\text{€}) = 120.00\text{€}$) and *Claudia* ($ivc_{Claudia} = 90.00\text{€} + (0.00\text{€} - 0.00\text{€}) + (0.00\text{€} - 32.75\text{€}) = 57.25\text{€}$) 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			
	<i>Aron</i>	<i>Bob</i>	<i>Claudia</i>
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 ($vc_{Aron}^{positively\ influenced} = 50.00\text{€}$) and on the other hand because *Aron* himself induces in turn negative social influence on *Bob* ($lvc_{Aron}^{negative\ influence} = 7.50\text{€}$). However, *Aron* regains value because of the negative social influence induced by *Claudia* on him ($lvc_{Aron}^{negatively\ influenced} = 20.25\text{€}$). *Bob* receives value contribution based on the one hand on the positive social influence induced on *Aron* ($vc_{Bob}^{positive\ influence} = 50.00\text{€}$) and on the

other hand he regains lost value contribution due to being negatively influenced by *Aron* and *Claudia* ($lvc_{Bob}^{negatively\ influenced} = 20.00\text{€}$). 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* ($lvc_{Claudia}^{negative\ influence} = 32.75\text{€}$). Please note that the overall sum of value contribution within 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 approach 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 neg-

ative 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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4 Conclusion

The final chapter of the dissertation provides an overview of both the major findings as well as limitations and future research perspectives of the two research topics which were the focus of this dissertation.

4.1 Major Findings

Communication between customers and companies and among customers in the context of modern business and society plays an important role for customers and companies alike. To take advantage of the possibilities provided by the digital revolution, companies began hosting their own firm-sponsored online customer networks (Lenka et al., 2016; Nüesch et al., 2015; Pozzi et al., 2016). In general, customers can no longer be regarded as independently acting individuals but rather as an increasingly connected and mutually influencing community of customers (e.g., Nejad et al., 2014). To address this issue, this dissertation focuses, on the one hand on customers participating in firm-sponsored online customer networks and how their social engagement activities influence their own and other **customers' profitability** (Topic 1). On the other hand, this dissertation aims at developing novel approaches to be able to calculate **the "true" value** of customers interacting in online customer networks by including direct and indirect as well as positive and negative social **influence into the calculation of the customers' value** (Topic 2). **In the following, the major findings of the dissertation are described.**

By investigating the in-depth relationship between **customers' social engagement activities** and customer profitability in the context of Topic 1, there is not a significantly larger number of social engagement activities observed for customers who also have revenues compared to customers who are merely participating in the online customer network of the direct banking institution under observation. This is in contrast to most of the existing literature concerned with the investigation of the general **relationship between customers' social engagement activities** in online customer networks and their profitability (Goh et al., 2013; Kim and Ko, 2012; Manchanda et al., 2015; Rishika et al., 2013; Zhu et al., 2012). By further analysing in-depth the relationship between different forms of social engagement activities and customer profitability, the dissertation reveals a significant difference between the various forms of social engagement activities. For example, a significant difference regarding **a customer's revenue is observed for posting an answer in a general public forum** in contrast to raising a question in a topic-specific financial forum. For the first social engagement activity, a merely moderate increase is observed while the latter activity indicates a higher customer profitability for the participating customers. This more specific focus on different forms of social engagement activities is also supported in most of the existing literature where studies observed, for example, a more than 10% rise in customer profitability due to

increasing social media activities of customers on a **company's fan page** (Goh et al., 2013; Manchanda et al., 2015; Rishika et al., 2013). Focusing further on the actual sentiment of **customers' social engagement activities**, the research observes that customers with an overall positive sentiment are, however, not generally the main driver of customer profitability. In fact, customers with a negative overall sentiment concerning their social engagement activities seem to have in average a significantly higher revenue. These surprising results contradict general expectations about the positive correlation between the sentiment of **customers' social engagement activities** and their profitability (Bernhardt et al., 2000; Ittner and Larcker, 1998; Gummerus et al., 2012; Zhang et al., 2017). On the contrary, the findings indicate the importance of critical customers – hence customers who are perceived primarily with a negative sentiment. These customers can be beneficial for a sponsoring company for two reasons: First, they help to enliven discussions within the online customer network through their critical spirit and thus **trigger other customers' participation in these discussions** (Chen and Lurie, 2013; Garcia et al., 2012; Stieglitz and Dang-Xuan, 2013; Tsugawa and Ohsaki, 2017). Second, as the results of this dissertation indicate, customers with a negative overall sentiment generate a higher customer profitability. Therefore, although having a negative attitude, these customers seem to be financially valuable for a company. However, it must certainly be differentiated between the actual reasons for negative sentiment. With focus on practice, the dissertation therefore refutes assumptions about the general benefit of online customer networks for sponsoring companies. Currently, many companies focus on encouraging their customers to participate in their online customer networks, hoping that the rise in company-customer interaction will at the same time increase revenues and profitability. However, based on a comprehensive dataset, this dissertation indicates in the context of Topic 1 that an undifferentiated encouragement of social engagement activities may have no significant effect on customer profitability. Companies **should in general inspire customers to actively participate in the company's online** customer network and should at the same time provide possibilities for customers to perform different forms of social engagement activities such as, for example, the possibility to ask questions. Furthermore, companies should focus their attention not only on merely increasing **customers' participation**, but also on developing adequate managing tools in order to be able to **monitor the correlation between customers' social engagement activities and their** actual profitability. As the findings of this dissertation indicate, practitioners not only have to differentiate between various forms of social engagement activities, but also have to regard the impact of the positive in contrast to the negative sentiment of participating customers' **social engagement activities**.

In the context of Topic 2, the dissertation develops novel approaches to calculate the value of customers participating in online customer networks by including the actual customer-

specific revenue as well as direct and indirect network effects. These effects play an increasingly important role for the valuation of customers. Formerly isolated customers are nowadays frequently connected and thus **induce a mutual influence on each other's purchase decisions** (Kumar et al., 2013; Hill et al., 2006). However, existing approaches often ignore network effects when calculating a customer value or provide only inaccurate results because of **double counting customers' value contributions** (Kumar et al., 2010a; Weinberg and Berger, 2011). Therefore, to extend existing models, this dissertation proposes novel customer valuation models by integrating direct as well as indirect network effects into the calculation. To avoid double counting, the model alters the allocation of value contribution among customers and does not change the overall value contribution within the online customer network. Furthermore, in contrast to existing customer valuation models (e.g., Berger and Nasr, 1998), also direct and indirect network effects are considered in the calculation by avoiding double counting at the same time. Demonstrated and evaluated on the basis of a real-world dataset, this dissertation aims at supporting companies in a more accurate evaluation of their customer base in the context of online customer networks. While the first model developed for this dissertation focuses on the integration of direct and indirect social influence exerted among customers, it neglects at the same time a differentiation between positive and negative social influence. Therefore, in a further step, the dissertation accounts for the impact of negative social influence by proposing an extended model to account for direct and indirect as well as positive and negative social influence between customers participating in online customer networks. By calculating a customer-specific integrated value contribution, the approach allows for evaluation of the integrated value contribution of customers by preventing over- as well as underestimation of **customers' value contribution** due to positive or negative social influence exerted on them or induced by them. Therefore, this dissertation helps practitioners to consider the destructive power of negative social influence and the enriching power of positive social influence on **customers' purchase decisions and profitability**.

Based on the findings of this dissertation, companies are able to better understand the **relationship between customers' social engagement activities and their customer profitability**, how different forms of social engagement activities have varying influence on customer profitability, and also how the sentiment of customers' social engagement activities are related to their revenues. Furthermore, this dissertation helps practitioners to value customers participating in online customer networks according to their **"true" value** by integrating not only the value contribution generated by the customers themselves but also including direct and indirect as well as positive and negative social influence induced between customers.

4.2 Limitations and Future Research

With the investigation of social engagement in online customer networks as well as the development of novel customer valuation approaches in the context of online customer networks, this dissertation aims at providing findings and in-depth insights into these research areas. However, there are also limitations, which can serve as starting points for future research.

In the context of Topic 1, the dissertation is able to analyse the comprehensive dataset of an online customer network of a German direct banking institution. The dataset includes **information about both customers' social engagement activities as well as their profitability**. Although these data serve as a solid basis for the results of this dissertation, future research should aim at including other online customer networks into the research about the relationship between social engagement and customer profitability. Thus, the diversity of topics can be enhanced, since online customer networks are prone to be monothematic, such as the financial focus of the online customer network under observation (e.g., Muniz and O'Guinn, 2001). Furthermore, the investigation of industry-specific peculiarities in order to get a holistic view in this field of research can be included. Insights from more than one online customer network can help to improve the generalizability of the observed findings regarding the relationship between social engagement and customer profitability in online customer networks.

Although provided with extensive sales data in the form of credit card transactions, the analyses of this dissertation neglect the costs when considering customer profitability. Since a broader perspective exists in general, a more detailed view on customer profitability is desirable for future research. This might include all kinds of online and offline revenues made by customers. Naturally, this is quite a challenge in terms of data collection since linking online and offline purchases can be difficult and costly. However, a thorough picture **of customers' revenues in the context of online customer networks will help to get an even more detailed view on the relationship between social engagement and customer profitability**.

The dissertation observes significant correlations between social engagement activities and **customer profitability**. However, these correlations are not quite strong since customers' social engagement, though important, is only one among many factors influencing customer profitability. Apart from social engagement, past buying behaviour, customer-specific buying behaviour, or general factors like age or gender can also have a significant influence. However, the focus of this dissertation is on the investigation of social engagement activities **of customers' participation in online customer networks and not on forecasting customer profitability of some kind**. For future research, a thorough examination on how customer

profitability is influenced in the context of online customer networks is an interesting and important research focus.

The **in-depth analyses of the sentiment of customers' social engagement activities** of this dissertation tries to identify the positive, negative, or neutral nature of a given social engagement activity. However, when it comes to recognizing sarcasm, irony, or spelling errors, many text mining approaches have difficulties in identifying the correct polarity (Cambria et al., 2014; Karlgren et al., 2012; Kumar and Sebastian, 2012; Rill et al., 2014; Vinodhini and Chandrasekaran, 2012). One solution to this problem – although at the expense of increased application effort – can be a hybrid lexicon-based and machine-learning approach using a context-specific sentiment lexicon in combination with an extensive training set (Collomb et al., 2014). For sentiment analysis in the context of online customer networks, future research still has to develop a fast, accurate, and robust text mining approach which can also be used in practice. Furthermore, information about industry-specific context, language, and other specific circumstances should be included into the sentiment analysis in order to increase quality and accuracy of the results.

In the context of Topic 2, the dissertation develops novel approaches for customer valuation. Applying the design science research process, the applicability of the approaches is demonstrated and evaluated using a real-world dataset, or respectively an exemplary online customer network (Gregor and Hevner, 2013; Hevner et al., 2004; Peffers et al., 2007). However, a long-term evaluation of the approaches with data from an online customer network is an important next step for future research. Based on a real-world application, **the actual impact of the proposed approaches on companies' customer valuation can be examined in detail**. Furthermore, future research should focus on single aspects of each approach. One interesting aspect is, for example, the accurate determination of **customers' shares of (lost) value contribution tracing back to positive social influence exerted on other customers and negative social influence induced by other customers**. Depending on the **actual online customer network, how much of a customer's value contribution is in fact induced or lost due to positive or negative social influence must be evaluated**. Furthermore, general differences between positive and negative social influence or between different types of customers have to be analysed and **incorporated into the calculation of customers' integrated value contribution**. The answers to these questions help to further develop and refine the proposed approaches of this dissertation.

In fact, the general applicability of the novel approaches relies heavily on the availability of sufficient data about the customers participating in online customer networks (e.g., Kumar et al., 2010b). Firm-sponsored online customer networks must be able to collect the necessary data for the application of the novel customer valuation models. This includes data about customer-to-customer interaction like public forum posts and private messages as

well as customers' online and offline sales data. With focus on the continuous implementation of the novel customer valuation approaches into a firm-sponsored online customer network, it might be necessary to first establish a sufficient data foundation regarding customers' interaction in order to determine the variables for the direction, strength, and polarity of exerted social influence.

In general, this dissertation investigates on the one hand social engagement in online customer networks and on the other hand develops novel customer valuation models. In this context, this dissertation presents relevant findings as well as innovative approaches. However, it does not focus on combining both research topics. For future research, combining both topics could provide interesting insights into the valuation of customers participating in online customer networks as well as how positive and negative social influence exerted between customers can be considered when calculating an integrated valuation model. However, for future research, a further investigation of the results of this dissertation is necessary. An example is the treatment of negative social influence exerted by customers participating in an online customer network as strictly negative for the sponsoring company, as done in the work on RQ.5. When combining this research with the results of the work done for RQ.3, a contradiction arises since the results of RQ.3 indicate that customers with an overall negative sentiment have a higher customer profitability in general. Therefore, a more detailed and accurate assessment has to be made to analyse the real impact of a customer's negative sentiment: Is it directed against the company or its products itself? Does it affect other customers' purchase decisions negatively? Or is there no effect on customer profitability at all? The key to a precise calculation of a customer's integrated value contribution is thus in the interpretation of a customer's sentiment and its positive or negative network effects as accurately as possible. This will be an interesting task for future research and can comprise, for example, the research on how positive or negative social influence – necessary for the calculation of customers' integrated value contribution – can be determined on the basis of a sentiment analysis of customers' social engagement activities. In this context, an automated determination of customers' sentiment will also play an important role. Furthermore, the dissertation's findings on how different social engagement activities have a different influence on customer profitability should also be regarded when determining the variables for the customer valuation approaches.

In summary, the relationship between social engagement and customer profitability in online customer networks as well as a network-oriented customer valuation are vast research areas with still many possibilities for future study. Above all, the connection between many different research disciplines – for example customer evaluation, text mining, or SNA – as well as the relevance of the research questions for a modern, globally connected society renders the research about the dissertation's topics very interesting, while at the same time also quite challenging.

4.3 References Conclusion

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