Social Sharing Design

Vom Fachbereich Rechts- und Wirtschaftswissenschaften
der Technischen Universität Darmstadt

zur Erlangung des akademischen Grades
Doctor rerum politicarum (Dr. rer. pol.)

genehmigte

Dissertation

von Diplom-Kauffrau
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aus Udmurtien, Russland

Erstreferent:	Prof. Dr. Oliver Hinz
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Tag der Einreichung:	29.06.2016
Tag der mündlichen Prüfung:	02.08.2016
Erscheinungsort:	Darmstadt 2016
Hochschulkennziffer:	D17

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I. Heimbach

Darmstadt, den 29.06.2016

Foreword by Prof. Dr. Oliver Hinz

Irina Heimbach's dissertation examines the phenomenon of user-driven diffusion of information, particularly in the online context and in the domain of Online Social Networks (OSN). OSN, like Facebook, are nowadays an indispensable part of everyday life of many people around the globe. Facebook has by now more than one billion active people and, according to a study by the Pew Research Center, OSN are becoming increasingly important for people to acquire information like news.

It is therefore of the highest social and scientific interest to learn more about this phenomenon. Dr. Irina Heimbach explores drivers and obstacles for the information diffusion between humans through OSN, which she calls "social sharing".

She presents interesting and challenging research questions, acquired many interesting datasets and analyzes them with great diligence and rigor using state-of-the-art statistical models.

All essays address important and timely research questions and the breadth of the work is laudable: While most of the essays address concrete business relevant problems, the work also summarizes the opportunities, challenges and problems in this new digital era.

Her work was inspired by many talks with industry practitioners and refined through academic peer review processes. Irina Heimbach can be proud of many published journal and conference articles and certainly is one of the rising stars in the area of business data analytics.

I highly recommend this book to both practitioners and scientist who are working in the area of Social Media. It delivers a lot of theoretical insights and also innovative ways to deal with new analytical challenges. I wish the author all the best with this publication and I believe that the book will be a huge success!

Prof. Dr. Oliver Hinz

Technische Universität Darmstadt

Abstract

This dissertation studies the effects of sharing mechanisms and content characteristics on social sharing processes. Social sharing describes any exchange of resources available in a social system (news, products, ideas, behaviors, etc.). The dissertation consists of four empirical studies, each addressing a different research question.

The first empirical project focuses on the effects of user control over the sharing process, preservation of user's privacy, and symbolic expressions of self-focus. The results from a laboratory experiment and two field studies reveal that content sharing is negatively affected by sharing mechanisms that allow greater control over the sharing process, aim to preserve the user's privacy and express a self-focus.

The second research project investigates how the sharing mechanisms which allow the non-disclosure of the users' identity impact social sharing. The results show that content related to controversial topics are less likely to be shared on Facebook, whereas they are actively discussed on discussion boards.

The third research project analyzes how the payment of incentives influences the social sharing. The results of three field experiments show that the payment of incentives increases the number of consumer reviews. Moreover, paid customers write less positive reviews and are less willing to make recommendations to their peers.

The last study explores whether positive or negative content is shared with peers. The results show that the relationship between content's positivity and its virality follows an inverted U-shape.

Zusammenfassung

Diese Dissertation untersucht den Einfluss von Sharing Mechanismen und Online Content auf die Social Sharing Prozesse. Social Sharing beschreibt einen beliebigen Austausch zwischen Sender und Empfänger von Ressourcen (Nachrichten, Produkte, Ideen, Verhaltensweisen, etc.), welche in einem sozialen System verfügbar sind. Die Dissertation umfasst vier Forschungsprojekte, welche verschiedenen Fragestellungen nachgehen.

Das erste Projekt befasst sich am Beispiel von Facebook mit der Frage, wie die Nutzerkontrolle über den Informationsfluss, Mechanismen zum Schutz der Privatheit und der symbolische Ausdruck des Selbstbezugs die Verbreitung von Content beeinflussen. Die Ergebnisse eines Laborexperiments und zweier Analysen von Felddaten offenbaren, dass eine erhöhte Nutzerkontrolle über den Informationsfluss, die Mechanismen zum Schutz der Privatheit und mit dem symbolischen Ausdruck des Selbstbezugs einen negativen Einfluss auf das Teilen-Verhalten der Sender haben.

Das zweite Projekt widmet sich dem Thema wie Sharing-Mechanismen, die die Anonymität der Teilnehmer unterstützen, die Social Sharing Prozesse beeinflussen. Hierzu wurden Aktivitäten auf Facebook mit den Nutzeraktivitäten auf Diskussionsforen verglichen. Die Ergebnisse dieses Projektes stellen dar, dass Teilnehmer auf Diskussionsforen (anonym) eher bereit sind, ihre Meinung über kontroverse Inhalte mitzuteilen.

Das dritte Projekt befasst sich mit der Fragestellung, ob man Sender für ihre Aktivitäten inzentiveren soll. Die Ergebnisse der drei Feldexperimente demonstrieren, dass bezahlte Kunden eher bereit sind, Kundenrezensionen zu schreiben. Die bezahlten Kunden bewerten jedoch die Inhalte tendenziell schlechter, sind weniger bereit die Inhalte zu empfehlen und bewerten diese auch schlechter.

Das letzte Projekt geht der Frage nach, ob positive oder negative Inhalte verbreitet werden. Die Ergebnisse zeigen, dass der Zusammenhang zwischen der Positivität des Inhalts einer umgedrehten U-Form folgt.

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1 INTRODUCTION

1.1 Background and Motivation

In the course of the digitization and the increased usage of information and communication technologies (ICT), more and more social and economic processes take place in a virtual environment. We arrange meetings with our friends and colleagues without great effort, and regardless of the spatial and temporal barriers using tools like Doodle, online calendars help us to have good overview of job-related and private schedules, we alter our Skype status to "busy" when we do not want to be disturbed and we exchange our experiences and seek for social support in online communities. While we had to cut out or copy a newspaper article in the past if we wanted others to read it, we can nowadays easily send a link to an interesting article or a funny video per email to our friends, colleagues, and relatives or share them on *social media* - "information technologies […] which support interpersonal communication and collaboration using Internet-based platforms" (Kane et al. 2014) - like Facebook and Twitter. Such *virtualization* of the social and economic processes i.e., the transition to the processes where "the physical interaction between people and/or objects has been removed" (Overby 2008, p. 278), opens new research opportunities.

While "virtualizing" the interactions between the members of a *social system*, which is understood as a "a set of interrelated units involved in joint problem solving to accomplish a common goal" (Rogers 2010, p. 476), one is directed by the capabilities and restricted by the boundaries of ICT. The relation between the ICT and the social systems is characterized in two ways. First, ICT set boundaries in representing the social relationships and communication. If we consider social media networks as a virtual pendant to offline social networks, we notice that while in reality we order our relationships with other members of a social system along a continuum from very close friends to loose contacts, social media networks usually weigh all the relationships equally (like bidirectional "Friends" on Facebook). Such virtualization of our relations to the other members of a social system might then affect the flow of *content* – any resources (information, money, products, etc.) available in a social system (Kane et al. 2014).

Second, ICT might create, trigger, and exaggerate phenomena that are new in such virtual systems. For example, while reading a newspaper or buying clothes in a physical store, we mostly rely on the preselection of the editors (such as the publishing of the most important news in the newspaper in the "best" positions from the editors' perspective) or on the decision of a few store managers about what is fashionable. Nowadays, a reader of online news platforms is supplied with "the most popular" rankings or even gets personalized news (e.g., somebody who is interested in technology related articles gets more such articles displayed on the website) or, in online stores, a consumer is supported with search and recommender systems during the shopping process (Hinz and Eckert 2010). The provision of such "popularity" information influences the market outcomes. For example, consider the debate about whether such search and recommender systems foster the concentration of sales or rather redistribute them from blockbusters to niches (Anderson 2006; Brynjolfsson et al. 2011; Brynjolfsson et al. 2010; Hinz et al. 2011a). From the viewpoint of information economics, the provision of such information allows addressing problems related to the consumer's uncertainty about the product quality assuming the market signaling function (Spence 1973; Tucker and Zhang 2011).

A stream of research that analyzes such new phenomena is summarized under the umbrella of *social computing* – the "computational facilitation of social studies and human social dynamics as well as the design and use of ICT technologies that consider social context" (Wang et al. 2007, p.79). This dissertation focuses on the social communication and content sharing processes in virtual environments. Figure 1 classifies the research goals of the focal thesis into the three-pillar framework of social computing proposed by Wang et al. (2007). With respect to the applications domain, my research concentrates on the social media platforms, discussion boards and consumer reviews as forms of online communities. Within the technological infrastructure, I mainly focus on web technologies. Finally, with respect to the theoretical foundations, I synthesize frameworks from the field of social psychology, communication, social networks analysis and sociology.

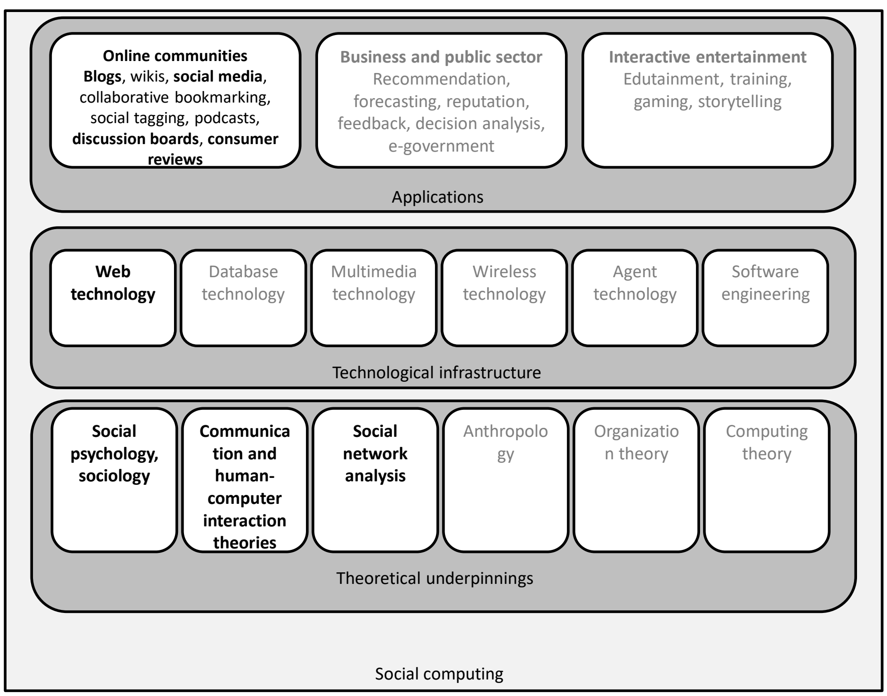

Figure 1. Social computing research paradigm (adapted from Wang et al. 2007)

Relying on the definition for innovation diffusion by Rogers (2010, p.5), content sharing refers to the process in which a piece of content is communicated through certain media over time among the members of a social system. *Communication medium* refers to "the means by which a message gets from a source to a receiver" (Rogers 2010, p. 217). On the other hand, content sharing on social media networks can be seen as a particular form of social communication as described by Hovland (1948) as "a process by which an individual (the communicator) transmits stimuli (usually verbal symbols) to modify the behavior of other individuals (communicatees)" (p. 371).

Social communication and interaction is integral to human life; it accounts for the diffusion of news, new products and services, ideas and practices, and it complements promotional efforts of companies and institutions (Bass 1969; Rogers 2010) resulting in increased sales (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004), in the adoption and discovery of new products and ideas (Berger 2013b; Coleman et al. 1957; Garg et al. 2011; Gladwell 2006; Rogers 2010; Ryan and Gross 1943; Susarla et al. 2012), in the change in individual and collective attitudes and opinions (Asch 1956), or in the influence of economic behaviors, such as bidding in online auctions (Hinz and Spann 2008). Since its acknowledgement as the main driving force of the spread of an innovation in a social system (Rogers 2010), marketers have been striving for intervention into such social processes, with the purpose to boost the adoption of products and services. In the early stages, the research on social communication in the marketing area focused on a product-related, one-to-one peer communication referred to as *word of mouth communication* (Arndt 1967; Brown and Reingen 1987; Dichter 1966). However, despite the recognition of its power, such word-of-mouth communication, due to its face-to-face nature, was very difficult to manage and measure. A closer look into the pioneering studies in this field reveals that the magnitude of such word-of-mouth communication on a new product diffusion was measured on an individual level mostly by putting into relation the occurrences of product-related conversations of the consumer in the past to the actual adoptions using surveys (see e.g, Arndt 1967; Brown and Reingen 1987). The research on the early stages of social communication research could therefore neither (1) give ex-ante answers about the most influential people in a social system nor (2) track the speed and dynamics of the diffusion nor (3) be at all able to run large scale field experiments with purpose to find the most successful design for word-of-mouth marketing (also called viral marketing) nor (4) have access to and to analyze the word-of-mouth conversations due to their oral nature.

Since the first studies, social communication has experienced tremendous development and embraces many other facets compared to the traditional understanding of word of mouth in the 60-80s. In the 2000s, the researchers therefore introduced the term of *electronic word of mouth* or "*word of mouse*," describing it as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau et al. 2004). Cheung and Thadani (2012) summarize such differences between the traditional word-of-mouth communication and its digitally enabled counterpart in "unprecedented scalability and speed of diffusion", as an asynchronous mode of communication, higher persistence and accessibility and increased measurability (p. 462). Online conversations now take different forms: consumer reviews – one of the most examined manifestations of such electronic word of mouth, blog posts, or referrals sent via email or social media platforms (Cheung and Thadani 2012).

The social communication in a virtual environment is distinct from its physical counterpart in many respects. First, one of the developments was the advent of Web 2.0 information technologies and thus of the *user-generated content (UGC)* that “comes from regular people who voluntarily contribute data, information, or media that then appears before others in a useful or entertaining way, usually on the Web—for example, restaurant ratings, wikis, and videos” (Krumm et al. 2008). UGC turned people into prosumers – producers and consumers - of the digital content. People write reviews about the restaurants they visited and products they bought in online shops (Chevalier and Mayzlin 2006); they share content they read via email with their peers (Berger and Milkman 2012); they take pictures and videos and upload them on different platforms (Zeng and Wei 2013); they forward promotional campaigns for crowdfunding projects (Thies et al. 2014) and online petitions (Felka et al. 2016; Panagiotopoulos et al. 2011). This strengthens the competition for the users’ attention (Dellarocas et al. 2015; Iyer and Katona 2015; Jones et al. 2004) and generates information overload (Toffler 1990). While some content disappears in the overwhelming stream of millions of uploaded videos, pictures, and posts, some content attracts high attention and becomes “viral”, catching on like diseases (Berger, 2013). An article in German online magazine Spiegel Online about a customer who has booked accidentally tickets to Bordeaux instead of Porto due to a misunderstanding earned a total of 42,679 Likes on Facebook and about 14,000 of them within the first six hours after online publishing, although this article was not placed prominently on the website of the magazine. The research however why some content becomes viral is rather scarce. A sole exception is the study by Berger and Milkman (2012) who find that positive and emotional articles are shared more frequently. Furthermore, articles which evoke strong emotions like anger and awe are shared more often. Although Berger and Milkman (2012) controlled for several factors and their findings are robust and confirmed in experiments and a field study, the research on drivers of content virality warrants further examinations.

Second, the soaring spread of social media - such as Facebook, Google+, or Twitter hauled the social communication processes to an unprecedented level. A recent descriptive study reveals that in 2015, articles in the 15 most popular German online newspapers and magazines prompted 116.7 million likes on Facebook, 4.3 million Tweets on Twitter, and 2.8 million plus-ones on Google (Schiller et al. 2016). Similarly, Pew Research Center reported in 2014 that about 30% of adults in the US get their news from Facebook (Anderson and Gaumont 2014), and in 2016 this number soared to 44% (Gottfried and Shearer 2016).

Third, people not only share their opinion (i.e., messages in terms of framework proposed by Hovland (1948)) about the products and services using ICT, but also the product itself, sending a link to a funny You Tube video or a news article. Rogers (2010), the father of innovation diffusion research, separates the word-of-mouth communication as a predecessor of the actual adoption of the innovation in his model. In social media, the temporal boundaries of these phases thus vanish or become very small. Consider e.g., Twitter, where people can share ("tweet") their opinions about some real events or physical products (i.e., sending the messages in the sense of traditional word-of-mouth research) but also spread the original messages of other users ("retweet"): The original message turns then to be the content itself. Moreover, Rogers (2010) strongly divides communication media into mass media (such as radio, television, newspapers) and interpersonal channels (face-to-face). As described above, the spread of UGC and social media has distorted this strict view on communication media (Hansen et al. 2011; Kwak et al. 2010). Sometimes the online conversations take place as dialogs between the consumers and marketers (see e.g., Goh et al. 2013). Therefore, in this dissertation I introduce the term "*social sharing*" describing any exchange of content and messages in different domains and thus integrating and extending the research on word-of-mouth communication and innovation diffusion. The term "*online social sharing*" refers to the interactions in Internet. In the Section 2.1, I will describe this framework in more detail.

The process of communication is moderated by *sharing mechanisms* (e.g., payment of incentives, choosing the audience size or even the communication medium). With purpose to facilitate social sharing activities marketers can design the sharing mechanisms, target the most influential people in social media networks, craft viral content and messages, etc. Therefore, I denote the deliberate choice and customized implementation of the different dimensions of sharing mechanisms, targeting of specific individuals as well as the purposeful crafting of content and messages the *social sharing design*.

1.2 Research Questions and Relevance

Digital content often gets shared through social media using *social plugins*, or pieces of program code provided by the social media that can be integrated into websites to facilitate users' interactions, such as Facebook's Like and Share Buttons. Figure 2 provides an example implementation on *The Guardian* website. Content-providing websites like this one voluntarily integrate customized social plugins to enhance their reach. The particular implementations of social plugins are then called *social buttons*.

Online content providers (e.g., newspapers, magazines) must choose among different designs of social buttons, which could affect users' social sharing behavior and, thus, key performance variables, including website traffic and company profits. Thousands of social media guidebooks offer valuable advice about how to increase website traffic and reach by connecting the site with social media through social plugins. Yet no structured analysis of sharing buttons design explicates why some content gets shared more and others not at all.

Consider, for example, the debate in Germany about privacy breaches through social plugins, in which personal data was gathered even from users who do not have accounts on the social media (Socialshareprivacy 2016; Zota 2014). It led some content providers to implement two-click designs: Users first activate the social plugin before being allowed to share content with peers on the social media (Figure 3). Although these practitioners were willing to respect users' privacy, they also risked losing some reach in the social media due to their two-click design.

Figure 2. Social buttons on the *Guardian* website

The effects on social sharing have not been established, just like the influence of different customizations of social plugins. For example, should content providers implement Facebook's Share or Like button, or both? How do these different design variants affect social sharing behavior? On the one hand, the more social plugins are integrated, the more the likelihood a content gets spread to different platforms. On the other hand, the website is cluttered with different buttons, which also lowers the likelihood. Therefore, content providers face a problem of choosing appropriate and the optimal amount of social plugins to maximize the social sharing.

Figure 3. Two-click buttons

Indeed, there is early evidence presenting the effects of sharing mechanisms on the social sharing processes. Studies by Berger and colleagues, Schulze et al. (2014) and Aral and Walker (2011) investigate, for example, different characteristics of the sharing mechanisms and emphasize the importance of these media for the diffusion outcomes. For example, Schulze et al. (2014) find that people are less willing to spread utilitarian apps on Facebook in contrast to hedonic apps, because users associate fun and entertainment with Facebook. Their findings suggest an interrelation between characteristics of the content and the characteristics of the sharing mechanism, a relation that has further aspects so far not studied in-depth. The research question is thus:

RQ1: *How does the design of sharing mechanisms influence the social sharing?*

The answer to this question might support those authors who are not willing to adapt or even purposefully craft content with the aim that it becomes popular and viral in different social media, the findings of this research can at least provide them with useful suggestions in selecting the appropriate communication medium for the message. For example if the content provider knows that Facebook users are interested more in funny and entertaining stories than in well-investigated, profound and polarizing articles, then it might focus in its social media strategy on other, more suitable, social media, rather than Facebook.

The next research question centers on the social sharing processes under anonymous mode. In social media networks, actors are represented by the profiles “that reflects the user’s identity in the network in ways consciously and unconsciously determined by the user (Kane et al. 2014, p. 286)”.Whereas in the face-to-face communication mode people reveal much of their identities, in other communication media the conversations could take place in anonymous mode. Therefore, the next research question is:

RQ2: *How does anonymity influence social sharing?*

For example, we currently observe the trend of the consolidation of communication media for online content providers, such as abolishing discussion boards and trying to transfer all discussion activities to one popular communication medium, e.g, to Facebook. Most websites, especially content providers like online newspapers and magazines and content aggregators maintain discussion boards where users have the possibility to comment or discuss diverse issues. The focus of such discussion boards is “on read[ing] and post[ing] messages that are sorted by date and subject, and also respond[ing] to discussion threads” (Fong and Burton 2006). Whereas such discussion boards were essential for the online content providers to interact with and to receive feedback from their users before the era of social media, some of them now consider consolidating diverse communication media on their websites, e.g., the Re/code[1] platform, or to change the policies as per like “Süddeutsche Zeitung”[2] and New York Times (Pérez-Pena 2010). As noted by Preece et al. (2003), the used technology shapes the character of online communities and the interaction between their members. Hence, a consolidation of communication media is questionable. Can the users of different communication media be pooled together without frictions? What are the costs of such a consolidation?

The next research question addresses the payment of incentives for social sharing activities. Strong interest in word-of-mouth marketing (viral marketing) is still based on the belief that product evaluations and recommendations from peers or spouses are more powerful and persuasive (Arndt 1967; Berger 2013b; Dichter 1966; Godes and Mayzlin 2004), more targeted (Berger 2013b) and have longer carryover effects (Trusov et al. 2009) than usual marketing instruments. For that reason, firms try to proactively generate and facilitate positive social

[1] http://recode.net/2014/11/20/a-note-to-recode-readers/

[2] http://www.sueddeutsche.de/kolumne/ihre-sz-lassen-sie-uns-diskutieren-1.2095271

sharing (Hinz et al. 2011b; Schmitt et al. 2011; Wangenheim and Bayón 2007) and offer monetary and non-monetary incentives for social sharing of word of mouth (coupons, rebates, and in-kind rewards). According to Pinch (2012) 85% of the Top 1,000 reviewers already received incentives for writing a consumer review. The effects of such incentivization are, however, less investigated. The question is thus:

RQ3: *How does the payment of incentives influence the social sharing?*

Finally, other research questions evolve around the content characteristics. Whereas the characteristics of the physical products that essentially influence their diffusion in a social system are well investigated (see e.g., Rogers 2010), little is known about the characteristics of the digital content such as videos, pictures, and online articles. Further, there is no consent in the previous research whether negative or positive content spreads in social systems. While some research recommends crafting positive content (Berger and Milkman 2012; Milkman and Berger 2014), other finds subtle nuances why the general proposition whether positive or negative content goes viral is not true (de Angelis et al. 2012; Hansen et al. 2011; Heath 1996). The forth research question is thus:

RQ4: *How are different content characteristics related to its likelihood to be shared?*

Understanding the reasons why some content becomes popular is of high relevance, as the media industry is challenged by the development of Internet-based services and has to face the transition of social life into the digital environment. First, an increasing number of readers substitute printed magazines and newspapers with online content which is currently often still free of charge. But as more and more media companies shift to freemium business models like the New York Times, knowledge about the drivers of content virality could be useful for sophisticated pricing strategies for online content. If publishers could predict the popularity of online content, they could increase revenues by charging higher prices for ads in popular articles. Moreover, the results might be generally adapted for designing successful viral marketing campaigns in multiple domains, like creating awareness for new products, political communication or crowdfunding projects.

1.3 Structure

In the following sections, I first summarize the state of the art of the social sharing research along the integrated framework of social sharing and elaborate research agenda of this dissertation. Hereby, I discuss how the conceptual models related to social sharing processes are translated into operational ones. The following empirical studies then address the research questions I outlined above. I present the results of four research projects each addressing these distinct research questions. The dissertation concludes with brief summaries of the projects, derives general theoretical and managerial implications and outlines the directions for further research.

2 SOCIAL SHARING

2.1 An Integrative Framework

For studying social sharing processes, I suggest a new framework that synthesizes the innovation diffusion model of Rogers (2010), social media networks of Kane et al. (2014) and the model of social communication proposed by Hovland (1948). This synthesis helps to combine the individual and the aggregated views on the social sharing process.

I distinguish between the three types of actors in a social system. The first group consists of *marketers* - private individuals or companies and institutions that are *interested in the diffusion of the content* (product, service, certain behavior). Content creators like bloggers or You Tube video makers also belong to this group. With respect to the sources of content, I thus distinguish between the *market-generated* and *user-generated* content. These actors can influence the social sharing processes by designing the content itself or the communication context, such as paying incentives for social sharing (e.g., for writing consumer reviews) or choosing the most suitable communication medium (e.g., advertising on Facebook or TV).

The second group is made up of individuals who consume the content (read news, download an app, buy books, etc.) and share their experience, e.g., via consumer reviews or even share the content itself (send a link to an online article or a video). Following the definition of social communication by Hovland (1948), a person, who sends a message (this corresponds to the *stimulus* in Hovland's model), is then called a *sender (communicator)*. A person who receives a message is the *recipient* or *receiver (communicatee)*. Senders' and receivers' characteristics and motives influence the willingness to engage in online social sharing processes. The senders of social sharing messages make decisions on the base of cost-benefit analysis (Gatignon and Robertson 1986). If the benefits of the social sharing outweigh the costs, the users will engage in such communication, and not if otherwise. The *responses* constitute the reactions of the receivers (audience) to the stimulus, i.e., decisions whether to receive the message, to consume the content and to share the experience with further audiences. Note that consumption does not necessarily trigger the social sharing process. On the aggregate level, we then observe how the majority of the population responds to such individual social sharing processes, manifested in sales, popularity rankings, etc. Furthermore, the same person could then take on different roles in the different stages of social sharing: The receivers become new senders, presenting the temporal development of social sharing processes.

Before the time of ICT, groups of marketers were examined rather independently from the social system, where the diffusion takes place (compare e.g., Rogers (2010), Bass (1969)). Nowadays ICT allows companies be involved into such social sharing. For example, on Facebook fan pages dialogs between the companies and the users take place (see Goh et al. 2013). Thus, with respect to the marketer's involvement in the social sharing processes, I distinguish between *organic* vs. *marketer-controlled* social sharing. Therefore, we can organize the previous research that builds upon the social sharing processes along the continuum on the marketers' involvement (see

Figure 4). *Customer referral programs* are “deliberately initiated, actively managed, and continuously controlled by the company, which is impossible or very difficult with organic word of mouth activities such as spontaneous customer conversations and blogs” (Schmitt et al. 2011, p. 47) and thus are related to the strongest form of the marketer’s involvement in the social sharing processes. Such customer referral programs have structured rewarding systems to reward both sides – the sender and the receiver. They usually apply monetary and non-monetary incentives to motivate people to engage in social sharing processes (Jin and Huang 2014; Ryu and Feick 2007; Schmitt et al. 2011; Wirtz and Chew 2002); I thoroughly discuss the effects of monetary incentives in the Section 2.7.9. Viral marketing campaigns (Aral and Walker 2011; Dobele et al. 2007; Hinz et al. 2011b; Koch and Benlian 2015; Toubia et al. 2011) are, in contrast, designed and set up by the marketer but usually do not stipulate a tight control of user activities like in customer referral programs. Finally, organic social sharing occurs spontaneously, offering no or very small opportunities for the marketers to intervene in the processes.

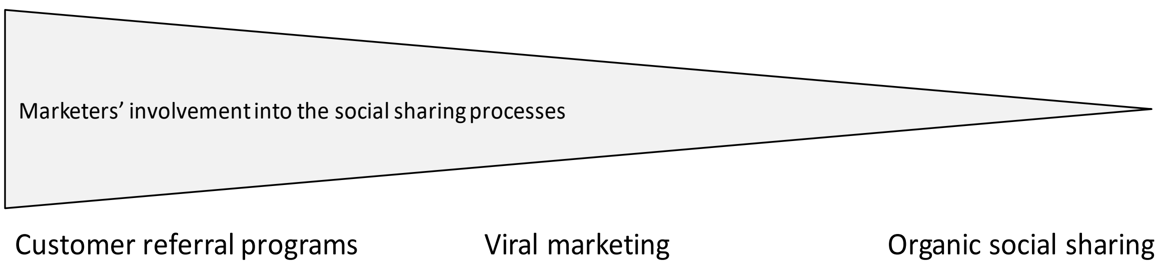

Figure 4. Continuum of marketers’ involvement into the social sharing process

There are some studies that address the issues of the marketer’s involvement in the social sharing processes. The studies by Wirtz et al. (2013) and Stephen et al. (2013) investigate how the disclosure of the payments for the users’ engagement in the social sharing processes affects the effectiveness of customer referrals programs and the writing of consumer reviews. The study by Goh et al. (2013) investigates how the marketer’s communication involvement influences the purchase behavior of users of a brand page on Facebook.

Some researchers introduce the term *deliberateness* that describes whether social sharing occurred on purpose or not. Thus, with respect to deliberateness, previous research identifies different forms of social sharing such as talking (see e.g., Arndt 1967; Coleman et al. 1957; Fitzgerald Bone 1992), telling, mentioning, referring (see e.g, Jin and Huang 2014; Ryu and Feick 2007; Schmitt et al. 2011; Wirtz et al. 2013), and making recommendations (De Bruyn and Lilien 2008; Leskovec et al. 2007; Van der Lans et al. 2010). Whereas talking, telling and mentioning could take positive or negative valence, referring and making recommendations imply a strong positive evaluation of the content. In cases where people are led by impression management motives they are more deliberate about what and how they share (Berger 2014). Referral programs and viral marketing campaigns try to trigger deliberate social sharing, offering monetary and non-monetary incentives (Godes et al. 2005; Hinz et al. 2011b; Jin and Huang 2014; Schmitt et al. 2011).

Whereas Rogers' (2010) model thoroughly discusses the effects of the characteristics of the innovation (this corresponds to content in the current framework) – "idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers 2010, p. 475) – and pays little attention to how people talk about such innovations, the model by Hovland (1984) focuses on the messages sent by senders and omits the content that should spread in the social system. In this framework, I introduce both elements and suggest distinguishing between content, i.e., that spreads in a social system, and messages the members of a social system share with each other about the content. I suggest doing this for several reasons. First, message characteristics rely heavily on text-based analysis; they are less applicable to content analysis like videos and pictures. Second, in the online environment people often simultaneously share the content and the message about the content, in contrast to physical products, where the word of mouth precedes the actual adoption. Consider a case where a positively written news article triggers negative commentaries (i.e., messages) because people disagree for some reason with the author. Therefore, it is important to distinguish between what is spreading in the social system and how people talk about it. Third, the author of the message is the sender who consumed the content. In the case of digital content, it is mostly crafted by a third-party, like news articles or YouTube videos. This forms the main distinction criterion between the messages and the content. Thus, depending on the application area, the message could be *explicit,* like in the case of consumer reviews, or *implicit,* like when people send a link to an interesting article (the act of sharing, itself, contributes to the positive evaluation of the content). Therefore, *content popularity* describes the volume of content consumption. *Content virality* refers to how often it is shared. Last, as was mentioned in the introductory part, the message could become the content (as with Tweets and Retweets) because ICT allows creating perfect copies of messages.

Next, the framework is extended by *contextual factors*. The process of communication is mediated by *sharing mechanisms*. Whereas the fathers of innovation diffusion research Rogers (2010) and Bass (1969) strongly distinguish between mass media and interpersonal communication, we cannot nowadays make such a clear cut between the communication media: interpersonal communication takes place within social media, like Facebook, Google+, Twitter, and content aggregators like Reddit and Digg, and UGC providers YouTube, Instagram, and Flickr, etc. Such social media platforms serve as intermediaries between the marketers and the consumers and are highly interested themselves in the social sharing processes that take place on these platforms (Veit et al. 2014). The modern researchers face social sharing processes not only within a single social system but within multiple ones represented by the social media networks (Kane et al. 2014). Kane et al. (2014) elaborate four features of social media networks "such that users (1) have a unique *user profile* that is constructed by the user, by members of their network, and by platform; (2) *access digital content* through, and *protect* it from, various *search* mechanisms provided by the platform; (3) can *articulate* a list of other users with whom they share a *relational connection*; and (4) *view and traverse* their connections and those made by others on the platform.” Such social media can actively design the communication context so that the marketers can decide whether they make use of such opportunities to spread their content in a social system. I suggest the term sharing mechanism as opposed to keeping the established term “communication medium” because the modern communication media themselves offer different sharing mechanisms that intend and evoke different sharing behaviors (compare, e.g., the functionalities of Facebook’s Share and Like button, or putting/omitting “@” in Tweets on Twitter).

Other communication context characteristics refer to *time* aspects, *public mood* and *attention competition*. These contextual factors might have an influence on the components as well on their relationships e.g., the sender-recipient relationship or content related characteristics that might change over time.

In the following, I then describe the findings on the particular components of social sharing with the main focus on the sender, the receiver, the content, the message, the resulting receivers’ responses to the social sharing messages and sharing mechanisms and other contextual factors.

2.2 Responses

I start the description of the social sharing framework with the receivers' responses. Hereby, I distinguish between *individual* and *aggregated* levels of analysis as well as *positive* and *negative* responses. Receivers' *positive responses* refer to the outcomes that are intended and desired by the marketers; *negative* ones refer to outcomes that are rather undesirable or even detrimental for the marketers.

2.2.1 Positive responses

In the aggregated level analyses, social sharing activities might lead to increased sales (Godes and Mayzlin, 2004; Chevalier and Mayzlin, 2006; Asur and Huberman 2010; Dewan and Ramaprasad 2012; Dewan and Ramaprasad 2014; Lu et al. 2013; Rui et al. 2013); the adoption and discovery of new products and ideas (Berger 2013b; Coleman et al. 1957; Garg et al. 2011; Gladwell 2006; Ryan and Gross 1943; Susarla et al. 2012); on the decision making behavior (Bikhchandani et al. 1992; Hinz and Spann 2008); increased investments into crowdfunding projects (Thies et al. 2014) and signatures in support for online petitions (Felka et al. 2016); improved prediction on stock markets (Gottschlich and Hinz 2014; Nofer and Hinz 2015), etc. Other research concentrates on the speed and volume of social sharing (Lee et al. 2009), creating awareness and interest for content (De Bruyn and Lilien 2008), on the reach of social sharing (Tucker 2014; Van der Lans et al. 2010), persuasiveness (Tucker 2014), on companies' customer acquisition, development and retention activities (Bijmolt et al. 2010), increased visits on companies' website (Rishika et al. 2013), on sense making in Egypt revolution on Twitter (Oh et al. 2015), and better work performance (Wu 2013). Luo et al. (2013) find that social sharing activities such as blog posts and consumer reviews have high predictive power over a company's equity value. Moreover, they find that this predictive power is stronger than conventional metrics such as Google Search and web traffic metrics. Das and Chen (2007) developed an algorithm to extract valence form small investor discussion boards with purpose to predict market activities.

On the individual level, Cheung and Thadani (2012) summarize that the most investigated constructs are the assessment of the content's usefulness (e.g., Kumar and Benbasat 2006; Xia and Bechwati 2008) and credibility (e.g., Cheung et al. 2009; Park and Lee 2009), attitudes (e.g., Chu and Kamal 2008; Lee et al. 2008) and purchase intentions (e.g., Bickart and Schindler 2001; Huang and Chen 2006; Kumar and Benbasat 2006; Park and Lee 2009; Park and Kim 2008). Bickart and Schindler (2001) find that discussion forums are more powerful in generating content interest than marketer-generated sources of information (e.g., companies' websites).

Social sharing activities in the past might lead to increased sharing activities in the future. This effect is called *herding effect* or *positive feedback loops* (Huang and Chen 2006; Muchnik et al. 2013). The existence of such effects in empirical studies leads – if not controlled - to the overestimation of the effects. As discussed in the Introduction, herding effects are partially caused by the provision or visibility of "popularity" information.

2.2.2 Negative responses

Receivers' responses to social sharing can also be of a negative character. Whereas most of research analyzes the positive outcomes, such as increased sales, positive purchase intention and attitude change, little research concentrates on negative effects. For example, Krasnova et al. (2015) show that passive consumption of content posted by friends on Facebook negatively influences receivers' well-being. In the context of self-designed content, Hildebrand et al. (2013) find that allowing users to share their opinions on the self-designed content of other users lead to less unique self-designs, lower satisfaction with the final content and lower content usage. Leskovec et al. (2007) discuss that social sharing of word of mouth does not necessarily lead to increased sales, but they suggest how to identify communities where the effectiveness of such social sharing increases. Ma et al. (2014) report that pre-release piracy of movies damages revenues by 19% percent, as social media also facilitate such illegal sharing activities.

In context of public opinion research, Noelle-Neumann (1974) introduces the *spiral-of-silence-phenomenon*. This phenomenon describes peoples' reluctance to discuss controversial topics if they believe that their opinion does not comply with the majority's opinion. The existence of a spiral of silence has been shown in various empirical studies in the field of political communication; see for structured overviews studies by Glynn et al. (1997) and Scheufle and Moy (2000). Social media are believed to support democratic traditions or even seen as catalysts of social changes in North Africa and Middle East (Ghonim 2012; Oh et al. 2015). However, the spirals of silence can also arise on social media. According to Pew Research Center people were not willing to discuss Snowden-NSA-revelation on social media (Hampton et al. 2014).

Additionally, the studies on social sharing processes might suffer from different selection biases. For example, *underreporting bias* corresponds to the enhanced likelihood of engagement in social sharing of people who experienced extraordinary good or bad experience with the product or service (Hu et al. 2009; Koh et al. 2010). This underreporting bias occurs very often in the context of consumer reviews. In Section 5 I address, for example, how incentives influence senders' engagement in social sharing processes such as writing reviews and making referrals.

2.2.3 Measurement of the response-related concepts

Table 1 describes the response-related concepts, their definitions and their measurement in empirical studies. I reduced this summary only to two dimensions because of the vast variety of different concepts investigated in empirical studies. From all the considered empirical studies, I draw two conclusions. First, the studies using realized behavior such as real sales numbers, purchases, adoptions, etc. are rather scarce. Therefore, vast number of studies uses diverse approximations such as sales rankings or purchase intentions and attitudes. The usage of the last two concepts is based on the assumptions of the theories of reasoned action (Ajzen and Fishbein 1980) and planned behavior (Ajzen 1991).

Second, the research on the negative effects of social sharing constitutes an evolving stream. This is mainly due to unobservability of the negative responses. Unlikely to the positive responses, expressed intentions not to do something are more difficult to correlate with an unobservable unrealized behavior.

Concept	Definition	Measurement in empirical studies
Positive responses	*Positive responses* refer to the outcomes that are intended and desired by the marketers.	Real data (Aral and Walker 2011; Hinz et al. 2011b); Approximation by rankings (Berger and Milkman 2012; Chevalier and Mayzlin 2006); Intention to purchase (Bickart and Schindler 2001; Huang and Chen 2006; Kumar and Benbasat 2006; Park and Lee 2009; Park and Kim 2008); Intention to share word of mouth (Barasch and Berger 2014; Berger and Iyengar 2013; Chen and Berger 2013) etc.
Negative responses	*Negative responses* refer to outcomes that are rather undesirable or even detrimental.	Self-reported decreased subjective well-being (Krasnova et al. 2015); Self-reported decreased intention to discuss (Noelle-Neumann 1974)

Table 1. Measurement of response-related concepts

2.3 Sender

In the following section, I describe how the senders shape the social sharing processes. With respect to the sender characteristics, I distinguish between *socioeconomic characteristics*, *personal traits*, *communication behavior*, and characteristics describing *structural positions* in the social networks as well as the *motives* and *costs* of engagement in social sharing.

2.3.1 Socioeconomic characteristics

Among the group of senders, the consumers who first discover the content and introduce it to the social system are particularly important. A description of this type of first consumers, named innovators and earlier adopters, was proposed by Rogers (2010). With respect to the socioeconomic characteristics, Rogers (2010) describes the earlier adopter as having "more years of formal education", "more likely to be literate", having "higher social status", having a "higher degree of upward social mobility", and "having larger-sized units (farms, schools, companies)" (Rogers 2010, p. 288). With respect to age, Rogers (2010) reports inconsistent findings: some researchers report that earlier adopters are younger than later adopters, while other researchers find no significant differences. In an unpublished analysis of the innovator characteristics across 36 empirical studies Heimbach et al. (2016) find support for Rogers' description of the earlier adopters, confirming that innovators have higher status in terms of income. An interesting question then arises. Can the findings about the first users of physical content also be applied for the discovery and dissemination of digital content? In the online context, most of content is available for free. Whereas in the case of physical content, where a small share of population with high incomes insert new content into the social system, the consumption and sharing of digital content would not necessarily assume that the senders also have high incomes.

It is notable that older studies on the effects of social sharing of word of mouth and content adoptions mainly used women for the surveys because of their availability for phone-based surveys (see e.g., Pessemier et al. 1967). Nowadays, the researchers have access to more representative samples.

Previous research finds subtle gender differences in the social sharing behavior. Wood (1966) find that female speech is more emotional and male is more factual. Further, men use more words. Whereas in the beginning of the 20th century, men speak about business and money, and women about clothes and men (Landis and Burtt 1924), seventy years later the differences between the genders with respect to conversation topics vanished (Bischoping 1993). The recent study by Skiera et al. (2015) shows that women engage more in social sharing processes than men and they might pursue different goals when using social media. Dobele et al. (2007) find that men are more likely to forward disgust- and anxiety-based content. Socioeconomic characteristics like age, gender, education, income and profession are usually included as controls in most empirical studies.

2.3.2 Personal traits

Personal traits describe “enduring patterns of thought, feelings, and actions; [] they show some degree of cross-situational consistency” (McCrae and Costa Jr 1999). Then, with respect to the personal characteristics, earlier adopters are assumed to have “more empathy”, be “less dogmatic “ and “less fatalistic”, “have greater ability to deal with abstractions”, “greater rationality”, “more intelligence”, and have favorable attitudes toward change and science. They are better able to deal with uncertainty, and “have higher aspirations (for formal education, higher status, occupations, and so on)” (Rogers 2010, p. 289-290).

In contrast to generalizing descriptions of the earlier adopters by Rogers (2010), the Five Factor Model offers a structured tool for characterizing personality (Costa and McCrae 1992). This personality inventory embraces the dimensions *neuroticism*, *extraversion*, *agreeableness*, *openness*, and *consciousness*. Moore and McElroy (2012) analyze the content that users share in their Facebook profiles and relate them to personality characteristics measured by the Five Factor Model. Yarkoni (2010) analyzes about 700 blogs and shows what the writing style reveals a lot about the personality traits of the bloggers. Qiu et al. (2015) analyze selfies – “self-portraits taken by oneself using a digital camera or smartphone” for sharing on social media. They find that, for example, a duckface, “a facial expression made by pushing lips outward and upward to give the appearance of large and pouty lips” (Qiu et al. 2015), of the selfie’s owner indicates a negative loading on the consciousness and positive on neuroticism.

Although the Five Factor model offers an extensive means to describe personal traits, the research on social sharing in marketing settings picks rather specific dimensions out like altruism (sub-dimension from agreeableness), extraversion, the need to be unique, the need to belong, and curiosity. Ho and Dempsey (2010) find out that more individualistic and altruistic people share more online content than others. Chiu et al. (2007) find that people with high scores on the extraversion and openness scales and low scores on consciousness scale were more likely to be involved in the social sharing process. Mantymaki and Islam (2014) find that social sharing on Facebook is significantly related to the exhibitionistic pre-disposition of the users. Further, motives to share content and word of mouth messages are related to the altruism as some people want to help others to make good decisions or prevent them from making wrong decisions (Phelps et al., 2004; Mazzarol et al., 2007; Ho and Dempsey, 2010; Dichter 1966; Sundaram et al. 1998). This becomes evident as content with high practical utility is shared rather often (Berger and Milkman 2012; Milkman and Berger 2014). However, Berger (2014) opens a discussion about whether the social sharing processes are driven by the altruism or rather self-serving needs of the sender. He argues that the sharing of useful content might “make people look smart and helpful” or “generate future reciprocity” (Berger 2014, p. 597). This is in line with the view of interpersonal communication by Gatignon and Robertson (1986) who build on the social exchange theory (Blau 1964). The core idea of the exchange theory is reciprocity that predicts the continuance of social interactions only if they are mutually rewarding (Gatignon and

Robertson 1986). Therefore, exchange theory cannot explain social sharing occurrences for fully altruistic reasons. This, still unresolved question opens another area for future research.

Additionally, I expect that selection processes take place in social sharing processes, i.e., that a particular group of people start the social sharing processes and keep them going. Research in this area could be substantially extended.

2.3.3 Communication behavior and structural characteristics

With respect to communication behavior, earlier adopters participate more in social life, are more interconnected through interpersonal networks, are more cosmopolite, have more contact to change agents, have greater exposure to mass media and interpersonal communication; they actively seek information about new content, have greater knowledge about the innovative content and are rather opinion leaders (Rogers 2010, p. 290-292). Johnson et al. (2015) find that opinion leaders use simple language that is familiar to other members of a social system.

With respect to the structural characteristics, market-level research seeks to identify influential people in social systems and to design optimal viral marketing seeding strategies (Dou et al. 2013; Hill et al. 2006; Hinz et al. 2011b; Katona et al. 2011; Richardson and Domingos 2002; Trusov et al. 2010). Here, one distinguishes between the *hubs*, people who have many connections in a social network, the *bridges* who connect different parts of the network and the *fringes*, people who build “impasses” in a network. The hubs and the bridges are supposed to strongly influence the social sharing processes (Hinz et al. 2011b).

2.3.4 Sender’s motives to engage in social sharing

The motivations to engage in social sharing processes might be intrinsic or extrinsic (Godes et al. 2005). Extrinsic motivators such as monetary and non-monetary incentives (Biyalogorsky et al. 2001) are discussed in Section 2.7.9. While describing the sender’s intrinsic motives to engage in social sharing processes, I mostly rely on the structured literature review by Berger (2014), who did an excellent work summarizing the previous research on individual motives to engage into the social sharing processes. He identifies 1) *impression management*, 2) *emotional regulation*, 3) *information acquisition*, 4) *social bonding*, and 5) *persuading* as social sharing functions. A particular instance of social sharing could be driven by several motives (Berger 2014, p. 588).

Impression management describes the sender’s motive to make a favorable impression on his or her audience and embraces three components 1) *self-enhancement* 2) *identity signaling* and 3) *filing the conversational space* (Berger 2014, p. 588). People want to appear knowledgeable and smart (Barasch and Berger 2014; Berger and Iyengar 2013; Berger and Milkman 2012). Berger (2014) infers that impression management would lead people to share content that is entertaining, useful, self-concept relevant, high status, unique, common ground and accessible. Further, as people want to present themselves in a positive light, impression management would shape content valence. Alexandrov et al. (2013) find that self-enhancement leads to social sharing of positive messages and self-affirmation to negative ones. This is consistent to the findings by de Angelis et al. (2012). Goes et al. (2014) examine how the possibility to subscribe to other users foster the social sharing on a consumer reviews platform. Moreover, they find that users write more objective reviews. Similarly, Toubia and Stephen (2013) show that people are mainly led by image-related utility when using Twitter.

Emotional regulation pertains to the human management of emotions (Berger 2014). If somebody experiences emotional events, there is a need to share these emotions (Rimé 2009). Berger (2014) summarizes different ways of emotional regulation that constitute of (1) *generating social support*, (2) *venting*, (3) *facilitating sense making*, (4) *reducing dissonance*, (5*) taking vengeance*, and (6) *encouraging rehearsal*. Nyer (1997) shows that angry consumers are more likely to share negative messages. Bowman and Narayandas (2001) investigate how the customer-initiated contacts trigger subsequent social sharing of experience.

Information acquisition pertains to the fact that people actively seek information they need for making decisions. This motive is manifested in (1) *advice seeking* and (2) *resolving problems* (Berger 2014). Berger (2014) suggests that information acquisition would lead people to share messages about (1) risky, complex and uncertainty-ridden decisions and (2) decisions where information is lacking. Rumors and gossip present "the informal exchange of information about contemporary social events, including the behavior and character of either the speaker or of third parties not present" (Dunbar et al. 1997, p. 233). Their spread is attributed to the information acquisition motives of the sender and the receiver.

Social bonding refers to the desire to connect with other people. Berger (2014) suggests (1) *the reinforcement of shared views* and (2) *reduction of loneliness and social exclusion* as components of social bonding. Further, he predicts that social bonding drives the sharing of common ground and emotional content.

The last group of motives centers on the *persuading of others* (Berger 2014). This motive would lead people to share controversial and emotionally arousing content.

2.3.5 Costs of engagement in social sharing

Previous research mostly concentrates on motives to engage in social sharing no matter if positive or negative. This is mainly because of the observability and, thus, measurability of the realized occurrences of engagement in the social sharing processes. However, peoples' decision to engage in social sharing is a „function of the cost/ benefit analysis by the potential influencer" (Gatignon and Robertson 1986). As the sender's motives could be seen as potential benefits, the costs of social sharing are less investigated.

The most obvious costs related to the decision to engage in social sharing are *time* and *effort* spent on communication (Gatignon and Robertson 1986). Sundaram et al. (1998) and Gatignon and Robertson (1986) introduce the term of *social costs* such as the *acquisition of social obligations* and the *risk of providing inappropriate advice*. Such social costs pertain to how the attitude toward the sender and the relationship to the receiver might be affected as a consequence of a social sharing (Jin and Huang 2014; Wirtz et al. 2013). Especially in case of incentivized social sharing, payment of incentives adds a complexity into the sender's and receiver's relationship. Wirtz et al. (2013) discuss how the person's metaperception processes drive social sharing when he or she is incentivized for making referrals. They find that the senders, in the presence of incentives, assumed negative self-perception by the receivers. This effect attenuates for the strong ties. From the field of public opinion, the theory of the spiral of silence suggests that people are not willing to share their opinion on controversial content if they believe themselves to be in the minority and perceive *threat* or feel *fear of social isolation* (Noelle-Neumann 1974).

As the online social sharing is technology mediated, other type of costs emerge how the users perceive *the ease of use* (Venkatesh 2000) of the ICT. *Frictional costs* refer, for example, to disutility that emerges from conducting any online transaction (Hann and Terwiesch 2003; Spann et al. 2004). As shown in the area of name-your-own-price markets (Hann and Terwiesch 2003), frictional costs can be substantial and should not be neglected while designing online transaction and interaction mechanisms, be it social plugins or shopping processes in online shops. Chiu et al. (2007) find that people who have a broadband internet access were more likely to forward messages in contrast to people who have to use dial-up modems. With respect to the number of social buttons the online content providers should implement on their websites, they should keep in mind that every social plugin demands loading times, because it is usually implemented using Java-Script.

2.3.6 Measurement of sender-related concepts

Table 2 provides an overview of sender-related concepts, their definitions and their measurement in empirical studies. As previously mentioned socioeconomic variables are usually included as controls into the empirical studies. The same applies to the inclusion of personal traits, albeit previous research focuses mostly on some particular dimensions like altruism, need to belong and extraversion. A recent emerging stream of research tries to relate personality traits to people's "digital footprints" left in the Internet (e.g., Qiu et al. 2015; Yarkoni 2010) but with no specific purpose in mind. Utilization of this information and development of decision support for marketing purposes (e.g., targeting for viral campaigns) might open promising areas for future research.

Although Berger (2014) discusses several concepts related to sender's motives to participate in social sharing, a large part of them has not been tested in empirical studies. Moreover, previous research concentrates on the benefits gained through social sharing like venting negative emotions, self-enhancement or persuading others but neglected the associated costs like fear of isolation, other social or frictional costs.

Last, many concepts are assessed by experimental manipulation or by self-reported measures in surveys. To overcome the drawbacks of methods based on self-reporting, future research might develop text-mining-based metrics to measure the personal traits and underlying motives for social sharing.

Concept	Definition	Measurement in empirical studies
Socioeconomic characteristics	Describe senders' along the social and economic dimensions like age, gender, education, income, profession, etc.	Self-reported (Molitor et al. 2011; Skiera et al. 2015)
Personal traits	"Enduring patterns of thought, feelings, and actions; [] they show some degree of cross-situational consistency" (McCrae and Costa Jr 1999).	Self-reported on Likert scales (Ho and Dempsey 2010; Yarkoni 2010)
Opinion leadership	"The degree to which an individual is able to influence other individuals' attitudes or overt behavior informally in a desired way with relative frequency" (Rogers 2010, p. 475).	Self-reported (Johnson et al. 2015; Molitor et al. 2011)
Structural position	*Hubs* are people who have many connections in a social network, the *bridges* connect different parts of the network and the *fringes* are people who build "impasses" in a network.	Well-established social network analysis metrics like degree centrality and betweenness centrality (Hinz et al. 2014; Hinz et al. 2011b; Hinz and Spann 2008; Molitor et al. 2011)
Impression management	Refers to the ways how people present themselves to achieve desired impressions (Berger 2014)	Experimental manipulation (Barasch and Berger 2014; de Angelis et al. 2012); Self-reported (Alexandrov et al. 2013)
Emotional regulation	Refers to the ways how people manage their emotions (Berger 2014; Gross 1998)	Self-reported (Anderson 1998; Hennig-Thurau et al. 2004)
Information acquisition	Refers to actively information seeking behavior	Experimental manipulation (Chen and Berger 2016)
Social bonding	Refers to the desire to connect with other people (Berger 2014; Rimé 2009)	Occurrence of sharing of similar content (Zeng and Wei 2013)
Persuading others	Refers to the desire to persuade other people	No empirical studies
Fear of social isolation	Refers to the individuals fear to be socially isolated	Self-reported (see for review Glynn et al. 1997; Scheufle and Moy 2000)
Belief to be in minority	Perception of to which degree other people share one's opinion	Self-reported (see for review Glynn et al. 1997; Scheufle and Moy 2000);
Metaperception	The person's feel how the others think about him or her	Self-reported (Wirtz et al. 2013)
Social costs	How the sender's image changes in the receiver's opinion and how the relationship between the sender and receiver may be affected as a consequence of a social sharing occurrence	Self-reported (Jin and Huang 2014)
Perceived ease of use	The extent to which a person believes that using technology will be free of effort (Venkatesh 2000, p. 344)	No empirical studies
Frictional costs	Disutility that emerges from conducting any online transaction	Number of steps to complete the transaction (Hann and Terwiesch 2003; Spann et al. 2004)

Table 2. Measurement of sender-related concepts

2.4 Receiver

Every time people encounter a piece of content, they decide whether and to whom to forward it (Phelps et al. 2004). Generally, receiver could be described by the similar characteristics as senders. Therefore, I focus in this section on the sender-receiver relationship (1) *tie strength*, (2) *tie status*, and (3) *homophily* as dimensions that shape the social sharing processes.

2.4.1 Tie strength

Tie strength describes the grade of the dyadic relationship between a sender and a receiver and constitutes as a (linear) combination of the (1) amount of time, (2) emotional intensity, (3) intimacy, and (4) reciprocal services (Granovetter 1973, p. 1361). People share all kinds of content with strong ties (Chen and Berger 2013; Frenzen and Nakamoto 1993). Brown and Reingen (1987) show that messages received from strong ties were perceived as more influential. De Bruyn and Lilien (2008) show that messages from strong ties facilitated awareness and triggered more interest for viral marketing campaigns. Moreover, content received from close friends is more likely to be passed along (Chiu et al. 2007). In an analysis of retweeting behavior on Twitter, Shi et al. (2014) find, in contrast, that weak ties (proxied by the unidirectional followers) are more likely to engage in social sharing.

Strong ties might know better each other’s preferences and needs and thus could facilitate more targeted social sharing. However, the costs of social sharing might also increase. Therefore, people would rather refrain from sharing content and messages from which they are not 100 percent persuaded.

2.4.2 Tie status

Berger (2014) suggests that *tie status* also moderates the social sharing process. The sender may have *higher status* than the receiver (e.g., one’s boss or a very popular person) or *lower status* (e.g., less popular person or employee). People might be led mainly by the impression management motives if they share content with high status others (Berger 2014). Empirical studies about how the tie status shapes the social sharing processes are scarce. A single exception builds the study by Du Plessis and Dubois (2013), who report from two laboratory experiments that people share rather positive messages with receivers who were higher in status.

Tie status might also explain the findings by Shi et al. (2014) (described in the previous subsection) about why weak ties engage more in social sharing processes: Unidirectional followers on Twitter indicate the existence of different social status between the sender and the receiver. An example of Madonna’s Twitter account illustrates this notion: She follows only 51 people while being followed by about 1.2 Mio fans.

2.4.3 Homophily

Rogers (2010) states that social sharing occurs between the members of a social system who are similar, i.e., homophilous, to each other in social status (e.g., education, religion, etc.) and values (e.g. beliefs, attitudes). “*Homophily* is the degree to which a pair of individuals who communicate are similar” (Rogers 2010, p. 305). How the degree of homophily influences the sharing processes is unclear. Whereas Rogers (2010) describes homophily as an inhibitor for diffusion processes, other research shows that this is a main driver of diffusion. De Bruyn and Lilien (2008) find that demographic similarity has a negative influence on receivers’ decision processes in viral marketing campaigns. Bin et al. (2014) investigates how the investors are led by the “allures of homophily”, by their interactions with the virtual communities, although the interactions with people who are not similar would promise an access to a novel type of content. In contrast, Lee et al. (2009) find that heterogeneous ties respond quicker to viral messages.

2.4.4 Measurement of the receiver-related concepts

Table 3 summarizes the receiver-related concepts, their definitions and how these concepts have been operationalized in empirical studies.

Concept	Definition	Measurement in empirical studies
Tie strength	*Tie strength* describes the grade of dyadic relationship between a sender and a receiver and constitutes as a (linear) combination of the (1) amount of time, (2) emotional intensity, (3) intimacy, and (4) reciprocal services (Granovetter 1973, p. 1361).	By unidirectional/bidirectional links in Twitter (Shi et al. 2014); By the scale developed by Frenzen and Davis (1990)
Tie status	The relative position of the sender and receiver in a social ladder	Manipulation in the experiment (Du Plessis and Dubois 2013)
Homophily	The degree to which a pair of individuals who communicate are similar (Rogers 2010)	The distance between the individual opinion and the aggregated opinion (Bin et al. 2014); The distance between the sender and receiver along demographical and behavioral characteristics (Xiao et al. 2013)

Table 3. Measurement of the receiver-related concepts

2.5 Message

In this section, I discuss how people talk about different things. The most analyzed form of social sharing messages are consumer reviews, also called product or customer reviews (see for the structured reviews e.g., Cheung and Thadani (2012), Trenz and Berger (2013), Floyd et al. (2014), You et al. (2015)). Through a thorough literature study, I identify the following message related dimensions: *volume, (average) valence, variance, extremity, sidedness, readability, length, helpfulness, personal information disclosure,* and *message type*. Whereas volume, average valence and variance constitute measures for market-level (i.e., aggregate) analyses, *message valence, sidedness, readability, length* and *helpfulness* are included into individual-level studies. In the following, I describe each of the dimensions and the findings on them separately.

2.5.1 Message volume and valence

Message *valence* (or sentiment) refers to whether a message is positive, negative, or neutral (You et al. 2015, p. 19). A positive message "highlights the strengths of a product/service and encourages people to adopt a product/service" (Cheung and Thadani 2012, p. 464). Likes on Facebook could be considered as an implicit positive message about some content. In contrast, a negative message "emphasizes the weaknesses/problems of a product/service and thus discourages people to adopt them" (Cheung and Thadani 2012, p. 464). Message *volume* pertains to the number of social sharing occurrences (You et al. 2015, p. 19). Message valence and volume are the most investigated message dimensions. In their meta-analysis You et al. (2015) identify 51 studies that alone analyze the relation between the message volume and valence and sales utilizing observational data in the top marketing and information systems journals. The findings on the message valence and volume are not straight forward. Whereas e.g., Archak et al. (2011), Chevalier and Mayzlin (2006), Clemons et al. (2006), Dellarocas et al. (2007) find positive relationship between consumer review volume and sales, Chintagunta et al. (2010), Duan et al. (2008a) and Forman et al. (2008) find no support for this claim. Further, positive consumer reviews are positively related to sales (Chintagunta et al. 2010; Clemons et al. 2006; Dellarocas et al. 2007; Park et al. 2007); Liu (2006) find no effect on sales. Berger et al. (2010) find more nuanced results such that negative reviews indeed hurt the book sales of established authors but increased them for unknown authors providing evidence for the conventional wisdom "any publicity is good publicity". Moreover, You et al. (2015) infer from their meta-analysis that message volume elasticity amounts to 0.236 and valence elasticity amounts to 0.417 having the highest short-term elasticities of all other marketing instruments (with the exception of price elasticities). This finding again attests the importance of the management of "online chatter" for marketers. Clemons and Gao (2008) and Chevalier and Mayzlin (2006) find that an additional negative review has a larger impact on the sales decrease than an additional positive review on the sales increase. This is in line with the psychological literature that predicts greater weighting of negative information compared to positive information (Baumeister et al. 2001; Kahneman and Tversky 1979; Rozin and Royzman 2001).

With respect to message valence, individual level studies also report from ambiguous findings. Rosen and Tesser (1972) state that people are reluctant to send negatively loaded messages to prevent building a negative attitude towards their personalities, i.e., they do not want to be the "bearers of bad news". Conducting the series of laboratory experiments, de Angelis et al. (2012) concentrate on the ambiguous impact of message valence. They find that people tend to generate positive word of mouth about their own experiences but transmit negative news about the experiences of others. The driving force of such behavior is the self-enhancement need of individuals: the sender enhances his or her self-esteem while talking about his or her own positive experiences and the negative of others.

Some researchers consider the *message extremity* that describes how positive or negative a message is. The participants in six focus studies by Mazzarol et al. (2007) report from receiving both positive and negative messages but always with extreme values. Further, message extremity is positively related to message helpfulness (Cao et al. 2011; Pan and Zhang 2011); and to sales (Archak et al. 2011; Clemons et al. 2006; Dellarocas et al. 2007). Willemsen et al. (2011) find that extremity is negatively related to message helpfulness. Heath (1996) discusses two contradicting hypotheses - the centrality (people prefer moderate levels of valence) and the extremity (people prefer extreme messages). In the series of laboratory experiments, he finds that people prefer to share bad messages over good ones and moderate messages over extreme ones.

2.5.2 Message sidedness and variance

One-sided messages contain either only positive or only negative arguments (pros and cons); *two-sided* ones contain both (Cheung and Thadani 2012, p. 464). Contrary to expectations, that two-sided messages would be rated as more helpful, Schlosser (2011) find e.g., that they are negatively related to review's persuasive power and credibility. In contrast, Cheung et al. (2009) and Doh and Hwang (2009) suggest positive relationship between the message sidedness and its credibility.

Message variance is the counterpart to message sidedness on the market-level studies and is also known under several names like message polarity, argument diversity, message dispersion, and entropy. Sun (2012) analyzes the message *variance* and concludes that high variance indicates content where the user preferences are heterogeneous such that some like it and others hate it. Additionally, high message variance is positively associated with message helpfulness (Cao et al. 2011; Pan and Zhang 2011) and with sales (Archak et al. 2011; Clemons et al. 2006; Dellarocas et al. 20079. Chintagunta et al. (2010) find no effect of message variance on sales.

2.5.3 Other message characteristics

In the following, I discuss other message-related dimensions that are rather rarely addressed in the empirical studies. Forman et al. (2008) find, for example, that reviews containing reviewer's *identity-descriptive information* like real names, nicknames or geographical location are positively related to the message helpfulness and to sales. This is tightly related to the discussion in the Section 2.7.5 about how much people reveal from their identities in online communication setting and how does this impact the social sharing processes. Baek et al. (2012), Korfiatis et al. (2012), and Li et al. (2013) analyze the *helpfulness* of such messages. Further, readable (Korfiatis et al. 2012) and long reviews (Forman et al. 2008; Mudambi and Schuff 2010; Pan and Zhang 2011) are often seen as more helpful. Positive reviews are positively related to review length. Whereas other researchers simply include the message length (Korfiatis et al. 2012), Jones et al. (2004) use it as proxy to measure the message complexity.

Xia and Bechwati (2008) and Park and Kim (2008) include *message type* in their analyses and find that consumer reviews based on facts like content attributes (*factual*) – in contrast to those describing user's experience with the content (*experiential*) – are positively related to review helpfulness (Xia and Bechwati 2008) and to purchase intention (Park and Kim 2008). Only the study by Cheung et al. (2009) used *message consistency* that measures the deviation of an individual evaluation from the valence of previous messages. Willemsen et al. (2011) analyze *argument density* and *argument diversity*. Koch and Benlian (2015) investigate how the marketers should craft messages in the viral marketing campaigns and find that *personalized* messages that suggested *scarcity* of the content have larger impact on the first stage receivers of such messages.

The framework of interpersonal communication by Schulz von Thun (1981) suggests four message layers: *matter, self-revealing, relationship,* and *appeal*. Whereas the matter pertains to the message as it is ("The restaurant I ate at last night was awesome!!"), the other three dimensions pertain to their interpretative dimensions. Self-revealing dimension pertains to what the sender reveals about her or himself with the message (e.g., "I am smart, I make good choices!"); relationship dimension connects with the receiver (e.g., "Look, it wasn't such a bad choice!"), and finally the appeal is the call for action (e.g., "You should go there too!"). Admittedly, the framework by Schulz von Thun (1981) is mainly familiar to German academia, but the analysis of the social sharing messages under their interpretative aspects could be an interesting research area, as the previous research has mainly focused on the matter of the messages.

2.5.4 Measurement of message-related constructs

Summarizing the theoretical concepts related to the social sharing message and their operationalization, we see relative consistency in the measurement of the message volume and valence (see Table 4). With respect to the message variance, different studies applied different metrics. Therefore, caution is necessary while interpreting findings from different studies. Manually coded metrics are less applicable in the studies using large observational data. Moreover, we see that all the measurements relate to text-based messages. Considering that people also communicate using emoticons, an interesting research area would be how to automatically extract information from such emoticons. First attempts towards this area are made, for example, by Chin et al. (2016).

Concept	Definition	Measurement in empirical studies
Message volume	Number of social sharing occurrences	Number of consumer reviews for each product (e.g., Amblee and Bui 2011; Archak et al. 2011; Bao and Chang 2014a; Chintagunta et al. 2010); Number of blog posts (e.g., Dewan and Ramaprasad 2012; Dewan and Ramaprasad 2014; Gopinath et al. 2013; Stephen and Galak 2012) and blog mentions (e.g., Dhar and Chang 2009; Onishi and Manchanda 2012); Number of posts in newsgroups (e.g., Godes and Mayzlin 2004); Number of mentions in Tweets (e.g., Rui et al. 2013); Number of recommendations on social media (e.g., Thies et al. 2014)
Message valence	Whether a single message is positive, negative, or neutral	Calculated using the output of automated text mining tools e.g., LIWC (Pennebaker et al. 2007), SentiStrength (Thelwall et al. 2010), SentiWs (Remus et al. 2010); Manual coding (Barasch and Berger 2014)
Average message valence	Consumers' average evaluation of the content	Average star-rating (e.g., Amblee and Bui 2011; Archak et al. 2011; Bao and Chang 2014a; Chintagunta et al. 2010); Number of positive Tweets (e.g., Rui et al. 2013);
Message sidedness	One-sided reviews contain either positive or negative arguments (pros and cons); two-sided reviews contain both (Cheung and Thadani 2012)	Manually coded (Cheung et al. 2009; Schlosser 2011)
Message variance	Diversity of positive and negative messages	Variance or standard deviation of the average valence (e.g., Archak et al. 2011; Chintagunta et al. 2010; Clemons et al. 2006; Dellarocas et al. 2007; Sun 2012); Ratio of positive and negative messages (Doh and Hwang 2009); Fraction of 5-star and 1-star messages (Chen et al. 2011; Chevalier and Mayzlin 2006); Percentage of positive and negative messages (Cui et al. 2012; Ho-Dac et al. 2013; Jabr and Zheng 2013; Liu 2006)
Perceived helpfulness	How helpful is a review	The ratio of helpful votes to total votes (Forman et al. 2008; Mudambi and Schuff 2010; Willemsen et al. 2011)
Message readability	How readable/comprehensible is the message	Usually calculated using well-established readability indices: Cunning –Fog Index (Gunning 1952), Flesh-Kincaid reading ease (Flesch 1948), Coleman-Liau Index (Coleman and Liau 1975)
Message equivocality	How much information does a review provide	Measured by 1-5 star scale: 3 is equivocal, 1,2,4,5 unequivocal (Forman et al. 2008)
Message length	How long is the review	Measured by number of words (Jones et al. 2004); Number of sentences (Jones et al. 2004)
Identity descriptive information in message	How much the message reveals senders identity	Measured whether a sender provides his or her real name, nickname and geographical location (Forman et al. 2008)
Message type, message objectivity	Factual reviews focus on facts, such as product attributes; experiential on the experience a consumer made during the purchase (Xia and Bechwati 2008)	Manually coded (Xia and Bechwati 2008);

Table 4. Measurement of message-related concepts

2.6 Content

Following Kane et al. (2014), the *content* refers to the resources available in a social system (information, products, services, news). Whereas the characteristics of the physical content that essentially influence their diffusion in a social system are well investigated (see e.g., Rogers 2010), the characteristics of the digital content such as videos, pictures, and online articles are less investigated in comparison. With respect to investigated content, most of the social sharing research (with focus on the message) is conducted, for example, on digital cameras (Archak et al. 2011; Chen et al. 2011; Ghose and Ipeirotis 2011; Gu et al. 2012; Park et al. 2012), books (Bao and Chang 2014a; Bao and Chang 2014b; Chevalier and Mayzlin 2006; Forman et al. 2008; Hu et al. 2012; Li and Hitt 2008; Pathak et al. 2010; Sun 2012; Zhang et al. 2012), movies (Chintagunta et al. 2010; Onishi and Manchanda 2012; Rui et al. 2013) and music (Dewan and Ramaprasad 2012; Dewan and Ramaprasad 2014; Dhar and Chang 2009).

Digital content characteristics for their part are the least studied component of the social sharing. One of the earliest studies on viral marketing by Phelps et al. (2004) found that the most forwarded emails contain jokes and chain letters but they do not further differentiate between content characteristics. Previous research analyzed also the sharing of news (Berger and Milkman 2012; Hansen et al. 2011; Heath 1996), summaries of scientific discoveries (Milkman and Berger 2014), applications (Aral and Walker 2011; Schulze et al. 2014), e-petitions (Felka et al. 2016; Panagiotopoulos et al. 2011), political communication (Oh et al. 2015; Stieglitz and Dang-Xuan 2013), and videos (Dobele et al. 2007; Szabo and Huberman 2010). In the following, I discuss the content characteristics in more detail.

2.6.1 Valence and other emotional dimensions

Similar to the social sharing message, *valence* of the digital content describes whether it is positive, negative, or neutral. Whereas the research that investigates social sharing messages focuses mostly on the valence and valence variance, the researcher of digital content characteristics analyze more nuanced emotional dimensions. In their analysis of New York Times articles, Berger and Milkman (2012) include the dimension of e*motionality* that refers to the amount of all emotionally loaded words (i.e., positive and negative) in an article. They find that positively and emotionally written articles are likely shared via e-mail with peers. In another study, Milkman and Berger (2014) show that this finding also applies to positively written summaries of scientific discoveries. In the context of political communication, Stieglitz and Dang-Xuan (2013) find that emotionally loaded Twitter messages are more likely to be "retweeted". In contrast, Luminet IV et al. (2000) find in three experimental studies that participants who were exposed to intense negatively valenced situations engaged in more social sharing. Notably, whereas the communication research in general asserts that negative news earns more attention in terms of content popularity (Galtung and Ruge 1965), the findings on content virality suggest that negative news would not be shared with peers. This could be crucial for the social media strategy of content providers.

Previous research also analyzes the effects of particular emotions such as *joy*, *anger*, *sadness*, *disgust*, *awe*, *anxiety*, and *surprise* on the content's likelihood to be shared with peers. These emotions could be distinguished between high-arousal (anger, awe, anxiety) and low-arousal (sadness) (Berger and Milkman 2012). Anger describes "the response to personal offence or injustice" (Dobele et al. 2007; Scherer 2005; Scherer and Wallbott 1994). Berger and Milkman (2012) and Dobele et al. (2007) show that anger inducing content goes viral. Anecdotal evidence supports this notion. In 2009, a Canadian singer David Carrol witnessed how baggage handling employees broke his $3,500 guitar during his flight with United Airlines. After the flight, he wrote a song and published it on YouTube. This song became a hit on YouTube overnight.

Ambiguous findings center on the emotion *sadness* that describes a state of an individual's lack of not well-being stemming from the experience of a fearful event (Dobele et al. 2007; Scherer 2005; Scherer and Wallbott 1994). Berger and Milkman (2012) find that sadness inducing New York Times articles are less shared per email. They argue that sadness belongs to low-arousal emotions, thereby deactivating the readers to share an article. In contrast, Dobele et al. (2007) provide examples of successful sadness-based viral campaigns of charity organizations like the Red Cross. This is also supported by anecdotal evidences. For example, one of the most shared articles in Germany in 2013 reported about a drowned dog that went viral with 62,229 Likes on Facebook (Schiller et al. 2016). As argued in the section on the sender's motives, there are several psychological mechanisms that underlie social sharing. As pointed out by Dobele et al. (2007), sadness-based content should be handled with care and encourage social support and benevolence rather than guilt. Further, sadness might be accompanied by other emotions like anger and anxiety, such that it is difficult to separate all the effects within one content.

Anxiety or fear describes the state "when people expect a specific pain, threat, or danger"(Dobele et al. 2007; Scherer 2005; Scherer and Wallbott 1994). Berger and Milkman (2012) and Dobele et al. (2007) find a positive relationship between the content evoking anxiety and its likelihood to be shared.

Disgust expresses a "feeling of aversion" (Dobele et al. 2007; Scherer 2005; Scherer and Wallbott 1994). Berger and Milkman (2012) in their study of New York Times articles control this emotion but do not find any significant results. In contrast, Heath et al. (2001) and Dobele et al. (2007) find that people are more willing to forward disgusting urban legends and viral videos.

Also, positive emotions *awe*, *joy*, and *surprise* are positively related to content virality (Berger and Milkman 2012; Dobele et al. 2007; Teixeira et al. 2012). Surprise is experienced "when something is unexpected" (Dobele et al. 2007; Scherer 2005; Scherer and Wallbott 1994). Joy expresses the feeling "when a goal has been achieved, or a movement toward such an achievement has occurred" (Dobele et al. 2007; Scherer 2005; Scherer and Wallbott 1994). Awe is described "by a feeling of admiration and elevation in the face of something greater than oneself" (Berger and Milkman 2012, p. 194).

2.6.2 Cognitive dimensions

Whereas valence, emotionality and evoking specific emotions are related to the affective responses to the content, there are also dimensions that relate to cognitive appraisal. Such dimensions are *interest*, *usefulness*, *self-relevance*, *self-concept relevant*, *common ground*, *high status*, *accessibility* and *controversy*.

Interest is a strong predictor of the content's popularity and virality. Berger and Milkman (2012) and Heath et al. (2001) find that interesting content is often shared with peers. Chen and Berger (2016) analyzes how the content acquisition mode (received from others or discovered) influences on the subsequent sharing. They find differences in sharing behavior between the receivers (received the content from others) and the finders (discovered the content themselves). People who received the content from others forward only the content that is interesting; for the finders this effect attenuates.

Berger and Milkman (2012) find also that useful content is more often shared with peers. Schulze et al. (2014) find more subtle differences. They assert that Facebook is less suitable for viral marketing of utilitarian apps.

Berger (2014) suggests that people would like to share *self-concept relevant* content that signals the identity of the sender. For example, if somebody shares news about an opera opening night, the audience might infer that the sender is an opera fan. Additionally, Heath (1996) introduces *self-relevant* dimension, that describes that the concept is relevant to the senders and the receivers, e.g., like crime rate in the area where both live. Self-relevance is supposed to affect social sharing in a way such that people would share any messages regardless of its valence.

Further, Berger (2014) suggest that people often talk about things they have in *common* with the receivers. This dimension is highly related to the self-relevance suggested by Heath (1996). Therefore, I suggest integrating both concepts. Zeng and Wei (2013) find that users of the photo-hosting platform Flickr upload similar photos during the formation of a dyadic social tie.

People often share *unique* and *high status* content to make an impression. Both dimensions are related to the self-enhancement motives of people. As shown by Hinz et al. (2015), a conspicuous consumption of rare virtual goods, like in massive multiplayer online games, is related to investing in one's social capital.

Another dimension refers to the *accessibility* that describes the availability or observability of the content, such as how people would be very likely to speak about the food in a restaurant or complaining about traffic delays while waiting for a train or bus. Berger and Schwartz (2011) find that more accessible content is shared more. From their meta-analysis of 51 studies, You et al. (2015) report that content with low accessibility profits more from the social sharing of word of mouth.

Controversial content, defined as "one[s] on which people have different, often polarizing, opinions" (Chen and Berger 2013), might experience different social sharing behavior compared to non-controversial content. The seminal work by Noelle-Neumann (1974) demonstrates that people are reluctant to discuss controversial topics if they are in the minority or their opinion does not comply with the public opinion. Talking about controversial content could be very unpleasant, as people start to judge what other people think of them or their behavior, especially if the conversation partners hold opposing attitudes, e.g., on gay marriage, stem cell research, egg cell freezing, prenatal diagnosis, wearing fur, etc. This mental process is called meta-perception in social psychology (Laing et al. 1966). Generally, people strive to be liked by others and to conform to social norms (Bikhchandani et al. 1992; Kelman 1958).

Chen and Berger (2013) investigate how controversial content is discussed. They state that the relationship between the controversy of the content and its likelihood of being discussed is shaped by two distinct processes: interest and discomfort. Whereas controversial content is positively related to the likelihood being discussed through increased interest, it might, at the same time, be negatively related to the likelihood of being discussed through the increased discomfort. These effects are moderated by the anonymity and relationship closeness of the sender and the receiver. They show that anonymity weakens the negative effect of the increased discomfort by discussing controversial topics.

2.6.3 Measurement of content-related concepts

Analyzing the previous research in terms of measurement, I conclude that most of the concepts (especially various emotional dimensions) are measured manually by independent coders. This impedes the empirical testing of these dimensions in large-scale data analyses. Some features could be easily measured using automated text mining tools like LIWC developed by Pennebaker et al. (2007), SentiStrength by Thelwall et al. (2010) and SentiWS developed by Remus et al. (2010), albeit LIWC possesses the most extensive capabilities. Further, although some researchers discuss in conceptual studies the effects of content dimensions like novelty and self-concept relevance, these concepts have not been tested in empirical studies so far. Some content dimensions like interest and controversy lie extremely in the eye of the beholder so that they could be very difficult to measure, even using manual coding by independent raters.

Finally, most of the automated tools could be applied for text-based content. The development of tools for automated content analysis of videos and images could be an interesting area for future research. As the increasing number of social media, e.g., Instagram, Flickr or Pinterest, facilitates the sharing of images, the automated extraction of marketing-relevant information from such content could offer valuable foundation for designing of successful social media monitoring systems.

Concept	Definition	Measurement in empirical studies
Valence	Whether a content is positive, negative, or neutral	Difference between the shares of positive and negative words calculated using automated text mining tool LIWC (Pennebaker et al. 2007) (e.g., Berger and Milkman 2012; Milkman and Berger 2014); SentiStrength (Thelwall et al. 2010) (e.g., Stieglitz and Dang-Xuan 2013); Manually coded (e.g., Milkman and Berger 2014)
Valence extremity	How positive or how negative the content is	Manually coded (e.g., Heath 1996)
Emotionality	How emotionally loaded is the content	Number of all positive and negative words calculated using LIWC by Pennebaker et al. (2007)(e.g., Berger and Milkman 2012); Manually coded (e.g., Milkman and Berger 2014)
Anger	Extent to which a content induces anger	Manually coded by independent raters (e.g., Berger and Milkman 2012; Dobele et al. 2007)
Sadness	The extent to which a content evokes sadness	Manually coded by independent raters (e.g., Berger and Milkman 2012; Dobele et al. 2007)
Awe	The extent to which a content is awe evoking	Manually coded by independent raters (e.g., Berger and Milkman 2012)
Anxiety	The extent to which a content evokes anxiety	Manually coded by independent raters (e.g., Berger and Milkman 2012; Dobele et al. 2007); Number of anxiety-related words counted by automated text mining tools LIWC.
Disgust	The extent to which a content evokes disgust	Manually coded by independent raters (e.g., Berger and Milkman 2012; Dobele et al. 2007; Heath et al. 2001)
Joy	The extent to which a content is perceived as joyful	Manually coded by independent raters (e.g., Dobele et al. 2007)
Surprise	The extent to which a content is surprising	Manually coded by independent raters (e.g., Berger and Milkman 2012; Dobele et al. 2007)
Usefulness	The extent to which a content is perceived as useful	Manually coded by independent raters (e.g., Berger and Milkman 2012; Milkman and Berger 2014)
Novelty, uniqueness	The extent to which a content is perceived as novel	No empirical studies
Controversy	The extent to which a content is controversial	Number of quotes in discussion threads (e.g., Gómez et al. 2008); Manually coded (e.g., Chen and Berger 2013)
Interest	The extent to which a content is evoking interest	Manually coded by independent raters (e.g., Berger and Milkman 2012; Berger and Schwartz 2011; Milkman and Berger 2014)
Accessibility	Whether a content is top of mind because of public visibility and existence of environmental cues (Berger and Schwartz 2011)	Manually coded by independent raters (e.g., Berger and Schwartz 2011; You et al. 2015)
Triability	Whether the content is triable before consumption	Manually coded by independent raters (e.g., You et al. 2015)
Durability	Whether the content is durable	Manually coded by independent raters (e.g., You et al. 2015)
Virality	The likelihood to share	Whether a content made to the most emailed list Berger and Milkman (2012); Number of Retweets (e.g., Hansen et al. 2011; Stieglitz and Dang-Xuan 2013); The intention to share (Milkman and Berger 2014)
Popularity	How often content is consumed	Number of downloads (Schulze et al. 2014) Number of purchases (Chevalier and Mayzlin 2006)
Common ground	Things somebody has in common with others	Using cosine similarity between two photos on Flickr (Zeng and Wei 2013); Manually coded (Heath 1996)
Self-concept relevant	Self-related, “tells others who you are as a person”	No empirical studies

Table 5. Measurement of content-related concepts

2.7 Sharing Mechanisms

This section addresses how sharing mechanisms might moderate social sharing processes. The design of sharing mechanisms builds an evolving research stream within social sharing processes. Rogers (2010) categorizes communication media into *interpersonal/ mass media* and *localite/ cosmopolite*. Recent attempts to structure the sharing mechanism dimensions were made, for example, by Schulze et al. (2014) who proposed the classification by *broadcasting / narrowcasting*, *solicited/unsolicited*, *incentivized/non-incentivized*, and *from friends/from strangers* dimensions, as well as Berger (2014) who distinguishes between the dimensions *written/oral*, *broadcasting/ narrowcasting*, *sharing with weak/ strong ties*, *social presence*, and *synchronous/ asynchronous*. In this section, I integrate and extend these previous taxonomies and characterize the sharing mechanisms within the dimensions (1) *underlying communication medium*, (2) *audience size*, (3) *directedness*, (4) *synchronicity*, (5) *anonymity*, (6) *social presence*, (7) *communication privacy*, (8) *symbolic expression*, and (9) *paying incentives*.

2.7.1 The underlying communication medium

The evolution of online communication media, which started in 1971 with the invention of email and continued by listservers, bulletin boards, chat systems, instant messaging, Internet video, blogs and wikis (Preece et al. 2003), is now coined by the widespread usage of social media like Facebook, Twitter, and Google+. In the particular case of consumer reviews, You et al. (2015) find that the most investigated communication media pertain to consumer reviews on Amazon (e.g., Amblee and Bui 2011; Archak et al. 2011; Bao and Chang 2014a; Bao and Chang 2014b; Chevalier and Mayzlin 2006; Forman et al. 2008; Gu et al. 2013; Li and Hitt 2008; Park et al. 2012; Pathak et al. 2010; Sun 2012; Zhang et al. 2012); Yahoo! Movies (Chintagunta et al. 2010; Duan et al. 2008a; Duan et al. 2008b; Karniouchina 2011; Liu 2006); blogs (Dewan and Ramaprasad 2014; Dhar and Chang 2009; Gopinath et al. 2013; Onishi and Manchanda 2012; Stephen and Galak 2012), and Twitter (Rui et al. 2013). You et al. (2015) distinguish different communication media within the dimensions *expertise* and *trustworthiness*. Communication media covering specific product information are classified as *specialized* and those covering a wide range of products as *general*. With respect to platform trustworthiness, You et al. (2015) distinguish between *independent*, i.e., third-party and *retailers' site.*

Different communication media, like brands, could evoke distinct associations. For example, Schulze et al. (2014) find that Facebook is less suited to promoting utilitarian apps using broadcasting sharing mechanisms because users have joyful, entertaining expectations of Facebook, which conflicts with the utilitarian character of the products. Similarly, different communication media could attract different segments of population. Whereas Facebook, first introduced in 2004, could have attracted many heterogeneous users, newer social media, e.g., Google+, first introduced in 2011, might have other selection of users. Twitter is widely used for political communication in Germany and not for private usage as in the US. These differences in user composition might be manifested in the shared content. For example, Heimbach et al.

(2015) investigate how content characteristics impact the sharing likelihood of news articles on Twitter, Facebook, and Google+. In line with the previous research they find that sadness is negatively related to content virality in Twitter and Google+ while awe positively influences the likelihood of articles being "liked". Interesting and anger evoking content goes viral in all three social media being examined. Moreover, they find that Twitter and Google+ users seem to resemble each other with respect to their sharing of content related to business, politics, technology, and science.

Therefore, it is important to know who the users of the different communication media are and how they can be characterized by the content they share over the respective communication medium.

2.7.2 Audience size

Broadcasting describes social sharing with a large group of receivers and *narrowcasting* with a small group of receivers (Berger 2014, p. 599). Aral and Walker (2011) find that broadcasting generates higher peer influence on Facebook. Schulze et al. (2014) and Chen et al. (2015) report more nuanced findings. Chen et al. (2015) find that artists' broadcasting messages on MySpace were more effective in generating music sales, albeit only personal non-automated messages. Schulze et al. (2014) find that broadcasted messages from strangers negatively impact the diffusion of applications on Facebook; this effect attenuates for utilitarian applications.

From the technological perspective, ICTs enable addressing different audience sizes. Therefore, I introduce the term of *high control over the sharing process* that addresses senders' possibility to choose the audience while sharing content or message. For example, Facebook's Share button allows sharing with all friends, with a group, with a single person, etc. As discussed in Section 2.4, people share all kinds of content with close friends (Frenzen and Nakamoto 1993). Thus, not giving the senders a choice about the information flow could influence the sharing behavior, such that people will share only content that addresses large audiences, and thereby fostering the concentration of popular content. Consider a user who finds an interesting content related to some scientific discovery and has only few friends who would express interest in this content. If the focal user is not able to address only these few friends, he or she could refrain from sharing altogether, because the other friends would not have interest in it and might even feel spammed with irrelevant content.

2.7.3 Directedness

"Communication can be *directed* (addressed toward a specific person or people) or *undirected* (sent without a particular person or people in mind)" (Berger 2013a). For example, consumer reviews and YouTube videos are shared by the consumers without any specific receivers in mind. Directed sharing mechanisms are tightly related to narrowcasting, but there are subtle differences. Face-to-face communication is in most cases rather directed (Berger 2013a) – in an online setting the directedness might attenuate. Schulze et al. (2014) show that utilitarian applications experience positive effects on their diffusion on Facebook if promoted by direct messages from friends.

2.7.4 Synchronicity

Communication synchronicity refers to the length of the breaks between the conversational turns (Berger 2014, p. 600). For example, Berger and Iyengar (2013) find that asynchronous (e-mail, text posts) communication media give conversation partners an opportunity to select the most interesting topic or brand, whereas in synchronous (phone, face-to-face) connections, people discuss any topic that comes to mind. Analyzing social sharing in chat rooms, Zhenhui et al. (2013) find that in synchronous communication people reveal a substantial amount of private information.

2.7.5 Anonymity

Anonymity describes “the ability to conceal a person’s identity” (Smith et al. 2011, p. 996). Sharing mechanisms vary in degrees how much the sender and the receiver reveal from their identities (Kobsa and Schreck 2003). On Facebook and Twitter most people act using their real names; on discussion boards people often use pseudonyms.

Different research domains show how anonymity has both positive and negative effects on human behavior. Generally, people behave in a negative manner if they are not observed (Christopherson 2007; Davenport 2002; Moore et al. 2012). Anonymity is associated with aggressive behavior (Moore et al. 2012; Zimbardo 1969), bystander apathy (Latané and Darley 1969), flaming (Thompsen and Ahn 1992) and social loafing (Latane et al. 1979). Studies from the field of behavioral economics demonstrate that cues of being observed influenced the dictator’s generosity in dictator games, see for the reviews, for example, Burnham (2003), Haley and Fessler (2005) and Rigdon et al. (2009). Millen and Patterson (2003) find that social sharing under the identity disclosure setting fostered accountability and polite conversations.

In contrast, anonymous discussion boards can be used to encourage conversations about “difficult” topics in medicine (Makoul et al. 2010). Christopherson (2007) also associates anonymity with privacy and psychological well-being. Bernstein et al. (2011) report that anonymity fosters more intimate and open conversations. Chen and Berger (2013) show that anonymity weakens the negative effect of the increased discomfort by discussing controversial topics.

Although previous research shows that, under the identity disclosure setting, the outcomes of human behavior are more favorable for the welfare, like fair allocation of resources and donating more money for fund-raising campaigns, I hypothesize that social sharing processes are affected in such a way that controversial topics are threatened to be lost in the spiral of silence (Noelle-Neumann 1974). In Section 4, I present the results of the comparison of social sharing processes under anonymous (discussion boards) and non-anonymous (Facebook) conditions.

2.7.6 *Social presence*

Social presence describes the degree of the sender's and receivers' salience (Berger 2013a). Other researchers refer to this, as media richness (Trevino et al. 1987), audience salience (Berger 2014) or sensory requirements (Overby 2008). The social presence is the highest in the face-to-face communication such that the conversation partners perceive non-verbal cues beyond the message. In a virtual setting, ICT try to simulate social presence by several ways. For example, Facebook offers an opportunity to show faces of other people who also liked the content near to the number of Likes, see Figure 5.

Figure 5. Addressing social presence on the *Süddeutsche Zeitung* website

The effects of social presence on the social sharing processes are less investigated, compared to the effects in online collaboration and education. Trevino et al. (1987) find that managers prefer face-to-face communication (i.e., high social presence) to share equivocal messages. Positive effects of social presence have also been shown in group collaboration (Yoo and Alavi 2001), online education (Tu and McIsaac 2002) and shopping (Hassanein and Head 2007). Berger (2014) suggests that increased social presence leads to more impression management, emotional regulation and information acquisition of the senders.

2.7.7 *Symbolic expression*

Symbolic expressions determine how users interpret and react to sharing mechanisms, in that they reflect "communicative possibilities of a technical object for a specified user group" (Markus and Silver 2008, p. 623). Such symbolic expression embraces icons, colors, verbal labels or also shared attitudes towards the sharing mechanisms. A printer-icon on a website means that content could be printed after pushing such a button; an envelope-icon invites emailing the content. The meaning of such symbols is determined by culture and path dependence. According to media reports, Facebook abolished the "thumbs up" icon from its social plugins in 2013 to prevent any cultural misunderstandings because in most Western cultures a "thumbs up" gesture is a positive sign expressing approval or acceptance; in contrast, the gesture would offend conversation partners in some Middle East countries.

Schema congruency (Mandler 1982; Piaget 1932) is a theory that might explain the differences in the responses to different symbolic expressions. This theory postulates that human use heuristics (schemas) in the daily decisions to reduce complexity. The learning process then could be seen as a process of building schemas, with the language as a potential instance of a schema. In Section 3, I investigate how the symbolic expression of the word "Like" on the Facebook's social buttons influences social sharing processes.

2.7.8 Communication privacy

Communication privacy (visibility) refers to whether social sharing occurrence is visible to other people. Usually, all social media sites show how many users shared the content before. In case of discussion forums, the new reader could potentially read what other users said before (Cheung and Thadani 2012, p. 462). When one sees that a news article gained a large number of comments, one can infer that the news attracts a lot of discussions.

Such communication privacy might have different effects. Leonardi (2014) find e.g., that if the communication between the members in an organization is visible, the knowledge sharing is assessed to be more efficient because people see who communicated with whom and about what. Thus, communication privacy is then linked to an increased organizations' innovativeness.

On the other hand, communication visibility could lead to herding effects, an effect several times investigated in several domains (Huang and Chen 2006; Muchnik et al. 2013). Herding effects emerge when people rely on cues referred from the observable behavior of others while making their own decisions. Such herding effects might lead to sales concentration (Salganik et al. 2006) but also to the formation of particular public opinion (Noelle-Neumann 1974) and beliefs (Asch 1956).

Communication visibility could be seen very similar to anonymity, discussed in Section 2.7.5. However, these features differ from each other, such that communication visibility refers to the accessibility of the conversation between the users A and B to the user C, A and B can hereby disclose their identity or not. Communication in discussion forums is usually a visible communication where the users often have opportunities to hide their real identities. Communication in chat rooms, on WhatsApp or Google Hangouts is often anonymous and private.

Technologically, communication privacy could be realized on several ways. Bernstein et al. (2011) describes "bumb" and "sage" features on 4chan as means to foster communication privacy. Two-click design described in the Introduction represents the means to preserve privacy of the website visitors who do not want to share content on social media.

2.7.9 Paying incentives

Incentives are "direct or indirect payments of cash or in kind that are given to an individual or a system in order to encourage behavioral change" (Rogers 2010, p. 236). Although Rogers (2010) discusses several payment scenarios: adopter versus diffuser incentives, individual versus system incentives, positive versus negative incentives, monetary versus nonmonetary incentives, immediate versus delayed incentives (Rogers 2010, p. 237), the research on the effect of incentives on social sharing took off just two decades ago. Previous research finds that people are more willing to engage in social sharing if they are incentivized (Biyalogorsky et al. 2001; Jin and Huang 2014; Wirtz et al. 2013). Stephen et al. (2013) find that paying incentives can produce more helpful reviews but does not have an effect on the message's objectivity and positivity. The analytical model by Kornish and Li (2010) suggests that the optimal size of the referral bonus should be as high as the social costs associated with the referral.

Although there are some empirical studies on investigating different kinds of incentives on the consumers' engagement in social sharing activities, the effects of such incentivizing still need further investigations for several reasons. First, the role of incentives has been primarily investigated on the field of customer referral programs (e.g. Biyalogorsky et al. 2001; Jin and Huang 2014; Kornish and Li 2010; Ryu and Feick 2007; Schmitt et al. 2011) that offer incentives in exchange of bringing new customers and thus generating positive social sharing. Only the study by Stephen et al. (2013) analyzes how the receivers perceive consumer reviews written by paid reviewers. Second, many studies analyze different sizes and types of rewards (e.g., in-kind vs. coupons vs. cash) (Jin and Huang 2014; Kornish and Li 2010; Ryu and Feick 2007). There are only few studies that actually compare payment and non-payment conditions. Third, most of the studies apply laboratory experiments and thus analyze behavioral intentions instead of real behavior (Jin and Huang 2014; Ryu and Feick 2007; Stephen et al. 2013; Wirtz et al. 2013). Finally, in my opinion, the effects of incentivization of social sharing activities are complex. Therefore, in Study 5 I address these research voids and present the results of three field experiments.

2.7.10 Measurement of sharing mechanism-related concepts

Table 6 summarizes concepts related to sharing mechanisms and how they are measured in empirical studies. As the research on the effects of sharing mechanisms on social sharing constitutes an evolving branch, there are few empirical studies that tested different sharing mechanism characteristics. Most of the studies measure the effects of sharing mechanism characteristics by manipulation in laboratory experiments (e.g., anonymity, synchronicity or audience size) or through the coding (assumption) of the observational data. For example, Berger and Iyengar (2013) assume oral face-to-face communication as synchronous and written as asynchronous. To sum up, the effects of sharing mechanisms promise a valuable area for future research on the drivers and moderators of social sharing processes. In my opinion, this is especially important because the design of sharing mechanisms offers marketers the best means to leverage social sharing processes in terms of desired responses.

Concept	Definition	Measurement in empirical studies
Expertise	Communication media covering specific product information are classified as specialized and those covering a wide range of products as general.	Manually coded (You et al. 2015)
Trustworthiness	Independent, i.e., third-party and retailers' site (You et al. 2015).	Manually coded (You et al. 2015)
Communication medium	On which medium social sharing occurs	Coding of observational data (Heimbach et al. 2015; Szabo and Huberman 2010)
Audience size	Narrowcasting pertains to sharing with just one person; broadcasting to multiple people (Barasch and Berger 2014)	Experimental manipulation (Barasch and Berger 2014); Coding of observational data (Schulze et al. 2014) and field experiment (Aral and Walker 2011)
Directedness	*Directed* sharing is addressed toward a specific person or people; *undirected* implies without a particular person or people in mind (Berger 2013a)	Coding of observational data (Schulze et al. 2014)
Synchronicity	The length of the breaks between the conversational turns (Berger 2014, p. 600)	Experimental manipulation (Berger and Iyengar 2013) and coding of observational data (Berger and Iyengar 2013; Zhenhui et al. 2013)
Anonymity	The sender's and receiver's ability to conceal their real identities (Smith et al. 2011)	Experimental manipulation (Chen and Berger 2013)
Symbolic expression	Interpretation of sharing mechanisms	No empirical studies
Social presence	Degree of the sender's and receivers' salience (Berger 2013a)	Self-reported (Hassanein and Head 2007; Yoo and Alavi 2001)
Communication privacy	Whether social sharing occurrence is visible to other people	Number of previous sharing activities (Muchnik et al. 2013)
Paying incentives	Direct or indirect payments of cash or in kind that are given to an individual or a system in order to encourage behavioral change" (Rogers 2010, p. 236)	Experimental manipulation (Jin and Huang 2014; Ryu and Feick 2007; Stephen et al. 2013); Coding of observational data (Schmitt et al. 2011)

Table 6. Measurement of sharing mechanism-related concepts

2.8 Other Contextual Factors

In addition to sharing mechanisms other factors like *attention competition*, *time-related aspects* and *public mood* might moderate social sharing processes.

With respect to attention competition factors that moderate social sharing processes, You et al. (2015) identified the *industry growth* and *competition*. As the number of content providers increases, so does the options for the receivers what to buy, read, etc. (Davenport and Beck 2013; Dellarocas et al. 2015; Iyer and Katona 2015). In context of news aggregators, Dellarocas et al. (2015) find that providing accompanying images and lengthening of the content snippet increases the chances that the user choose this content when the number of similar content increases. Jones et al. (2004) analyze user communication behavior on the Usenet newsgroups and find that (1) users share simple messages and (2) respond with simple messages or even (3) quit with active participation when the volume of the conversation increase (*information overload*). Szabo and Huberman (2010) compare YouTube and Digg and find that user's attention for content decays on Digg more quickly than on YouTube.

Companies' marketing-mix activities (i.e., decisions on product, place, price and promotion) constitute another source of influence on the sharing behavior. While previously content was available for free, increasing number of news sites employ different pricing strategies to earn revenues (Chiou and Tucker 2013; Halbheer et al. 2013; Oh et al. 2016). Paywalls refer to the "charging for content that was earlier available for free" (Oh et al. 2016). Oh et al. (2016) show the negative effect of the paywall introduction on the social sharing activities. The choice of the position on the website where to publish the content is also essential for its popularity and virality (Berger and Milkman 2012; Heimbach et al. 2015). Also the number of accompanying images and videos increases content's appeal (Dellarocas et al. 2015; Heimbach et al. 2015).

With respect to *temporal aspects*, Chen et al. (2015) shows that timing plays an important role in artist's broadcasting activities on music sales. Berger and Milkman (2012), Heimbach et al. (2015) and Szabo and Huberman (2010) attest varying content consumption and social sharing activities with respect to the time of the day.

Prevalent *public mood* might affect the average valence of content being shared on social media networks. Kramer et al. (2014) conduct a natural experiment on Facebook's News feed and find out that emotions expressed on Facebook's News feed influence the mood of the receivers which subsequently influences again what people post.

2.8.1 Measurement of other communication context-related concepts

Table 7 provides an overview how other social sharing context related concepts are measured. Similar to the research on the effects of various sharing mechanism characteristics, attention competition, time and public mood constitute less investigated components in the social sharing processes.

Concept	Definition	Measurement in empirical studies
Industry growth	Describes whether the industry is rather growing or stagnating	Measured using historical sales data (You et al. 2015)
Competition	Refers to the competition of user's attention	Average number of competitors, e.g., from COMPUSTAT (You et al. 2015); Number of similar content (Dellarocas et al. 2015); Number of content published at the same day (Heimbach et al. 2015)
Marketing-mix activities	Pertain to companies activities with respect to product, price, place (position) and promotion (advertising)	Introduction of paywall (Oh et al. 2016); Publishing in prominent positions (Berger and Milkman 2012; Heimbach et al. 2015)
Time	Pertains to temporal aspects like time of the day, day of the week, month, etc.	Including controls for time of the day (Berger and Milkman 2012; Szabo and Huberman 2010)
Public mood	General mood state of population	Valence of previously shared content (Kramer et al. 2014)

Table 7. Measurement of other communication context-related concepts

3 SHARING BUTTONS DESIGN ON FACEBOOK

3.1 Introduction

This study investigates how the particular design of sharing buttons influences what people share on Facebook – one of the most popular social media networks. To examine the effects of different sharing buttons, I apply a framework developed by Markus and Silver (2008) to study the effects of ICT artifacts on user behavior. Social plugins, as *technical objects*, exhibit specific *functional affordances* and *symbolic expressions (*Markus and Silver 2008), which in turn might trigger distinct user behavior and affect content diffusion in various ways. In addition to the general purpose of the sharing buttons, namely, to facilitate information diffusion in social media, I suggest *control over the sharing process* (i.e., senders can decide how and with whom they share content) and *privacy preserving* features (i.e., two-click design) as functional affordances and *self-focus* (e.g., Facebook's Like button) as a symbolic expression. The sharing mechanism likely interacts with the characteristics of the content (Barasch and Berger 2014; Schulze et al. 2014), so I anticipate that content characteristics and the sender's personal traits might moderate the effect of the sharing mechanism design. For example, Facebook's Like button is probably poorly suited to sharing bad news (e.g., catastrophe, death of a prominent person). To study the effects of different sharing mechanisms on content sharing, I examine German press articles shared on Facebook. I choose Facebook as the study context because it is the most popular social medium in Germany and also provides social plugins that can be customized in various ways (https://developers.facebook.com/docs/plugins/), thus establishing natural variation across content providers. Figure 6 shows an exemplarily instantiation of a Like button.

I conducted two field studies and a laboratory experiment. The data set from the first field study provides natural variation in the implementation and use of sharing mechanism by German online newspapers and magazines. In the laboratory experiment, I then systematically varied the sharing mechanism design and content characteristics and control for the personal traits of the participants. Finally, the data set in a second field study, pertaining to an online newspaper that changed its sharing mechanism design on its website, enables to study the effects of this functional affordance using a single-subject variation.

In the next section, I then conceptualize different sharing mechanism designs and their possible effects on content-sharing behavior. In presenting the results of the laboratory experiment and two field studies, I briefly comment on the corresponding results. Finally, I summarize the findings, conclude with some implications for theory and business practice, discuss the limitations, and offer suggestions for further research.

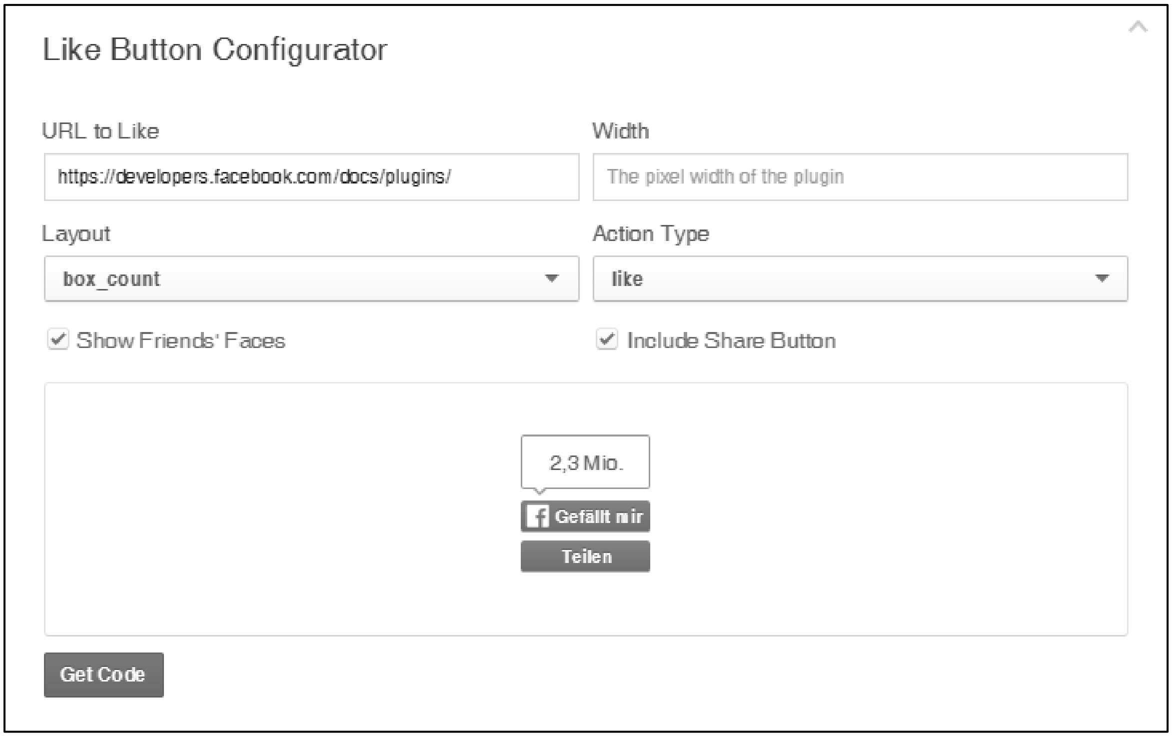

Figure 6. Sharing button instantiation on example of Facebook's Like button

3.2 Research Conceptualization

According to Markus and Silver (2008), ICT artifacts can be described by three concepts. The technical objects concept refers to the ICT artifacts themselves, whereas functional affordances and symbolic expressions pertain to the relations between users and those technical objects (Markus and Silver 2008). *Functional affordances* reflect the potential usage of the technical objects, including "the possibilities for goal-oriented action afforded to specified user groups by technical objects" (Markus and Silver 2008, p. 622), such as when social plugins enable users to share content online. Because both functional affordances and symbolic expressions are user-related, they might invoke different user behaviors, with distinct effects on the use of ICT artifacts (Markus and Silver 2008). That is, because users can interpret symbolic expressions of various sharing mechanisms differently, and various levels of functional affordances might exert different effects, I consider the design of sharing mechanisms a non-trivial task for social media business practitioners.

I identify several design issues that vary across content providers. The first is the implementation of the aforementioned two-click approach. The two-click design is a *functional affordance for privacy preservation*. The second issue revolves around the three design variants for Facebook's social plugins: Share, Like, and Recommend. Facebook actually offers two social plugins with sharing functionality, namely, the Like and Share buttons. The Like button implements a broadcast mechanism, which can be displayed with two labels: "like" or "recommend."[3] In

[3] In the following, I use quotation marks to refer to the symbolic expression; terms without quotation marks to refer to the technical object.

Markus and Silver's (2008) framework, the "like" and "recommend" buttons are identical technical objects and fulfill the same functional affordances (i.e., broadcasting content on Facebook), though their symbolic expressions differ. While the verb "like" is positively connoted and implies a focus of the sender's communication and attentional resources on him or herself ("I like something"; I define this congruently with psychological literature as *self-focus*, see e.g., Barasch and Berger (2014); Carver and Scheier (1978); Chiou and Lee (2013); Mor and Winquist (2002)), "recommend" is rather neutral and implies a focus on the recipients ("Recommended to you"; congruent with the psychological literature, I define this as *other-focus*).

When a user clicks the "Share" button, it provides more control over the process, such that the user may choose whether to share the content on his or her own timeline, on a friend's timeline, in a group, on a page he or she manages, or in a private message. The affordance of different possibilities for users' actions implies *high control over the sharing process*. Similar to "recommend," the verb "share" expresses an other-focus. Content providers can freely decide whether to implement the Like, Share, or both buttons and whether the sharing mechanisms should respect the privacy of other users who are not the members of the social medium. Table 8 summarizes the differences between the Facebook's sharing mechanisms with respect to the functional affordance of high user control and the symbolic expression of self-focus. In addition, I present the conceptual framework in Figure 7.

Technical Object	**Functional Affordance**	**Symbolic Expression**	**Sender Control over Sharing Process**	**Communication Focus**
Share button	A user has more control over the sharing process: where and with whom content is shared	"Share"	High	Other-focus
Like button	Content is shared with the user's whole social network	"Like"	Low	Self-focus
		"Recommend"	Low	Other-focus

Table 8. Implementations of Facebook's social plugins

Privacy preserving features might have three effects on users. First, two-click buttons could foster privacy awareness (priming) making users reluctant to share content. Second, with greater effort (one more click), the user might be less willing to share content on social media. Third, a herding effect might disappear. That is, a conventional one-click design allows users to see how many other people already have shared[4] the content, which offers clues about the article's popularity. Readers tend to share the most popular content, such that a herding effect or positive feedback loop emerges (Muchnik et al. 2013). Without this popularity information, users might be less likely to share. Generally, I expect that privacy preserving features hinder content diffusion, irrespective of the underlying user reaction.

[4] I use the term share and its derivation to denote any act of content sharing, regardless of the mechanism (i.e., "Share," "Like," or "Recommend" buttons).

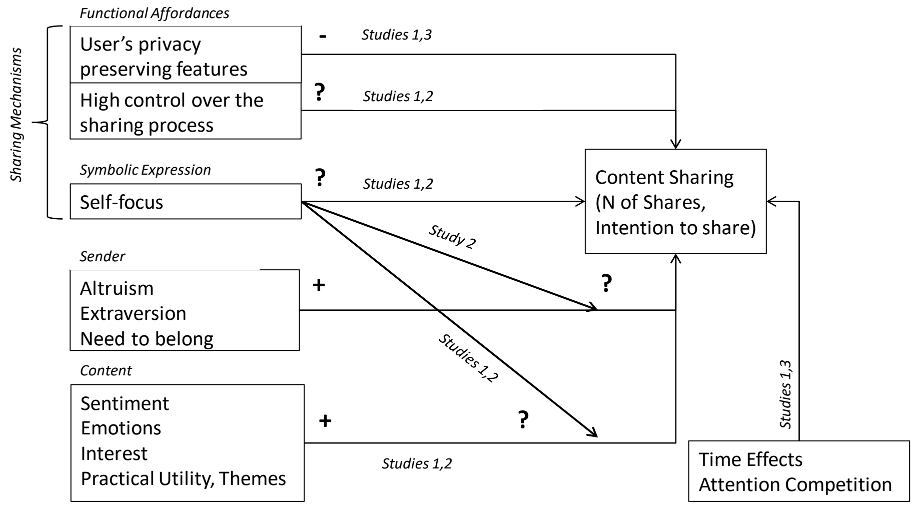

Figure 7. Conceptual framework for investigating the effects of different sharing mechanisms

Clicking a Like button broadcasts the content to the user's friends on Facebook, but the Share button allows more control over the process, because the user can choose with whom, where, and with what commentaries (message) the content should be shared. The effect of this high user control likely is not as straightforward as that of the privacy preserving functional affordance. The feature demands more cognitive effort from the user, which might lead to greater reluctance to share the content. Although a Share button also can be used to produce outcomes similar to those achieved with the Like button, it might narrow the content reach and thus decrease subsequent shares on Facebook (Aral and Walker 2011). Furthermore, sharing mechanisms with high user control facilitate differentiated selections of the topics shared, which could increase the chances that niche topics get shared on social medium. The aggregated effect of high user control over the sharing behavior is thus unclear.

The effect of a self-focus expression, as manifested in the use of the "like" button, is also unclear. On the one hand, if users are driven by self-manifestation motives to share content (Berger 2014; Hennig-Thurau et al. 2004; Ho and Dempsey 2010), mechanisms that express self-focus would better serve those motives and foster content sharing. On the other hand, if users share content for altruistic reasons (Hennig-Thurau et al. 2004; Ho and Dempsey 2010), the effect of self-focus expressions might negatively affect the content diffusion, due to a simple probability calculation. Imagine two persons, one altruistic and the other narcissistic, who do not like some topic. The altruistic person still might share this content, using a "Share" or "Recommend" button, because some of his or her friends could be interested in the topic. A narcissistic person does not care about the interests of others and thus is unlikely to share the content. Thus, this difference in symbolic expression should interact with users' motives and personality traits and have a negative effect on content sharing, through the limited content diversity.

Previous research also cites an uncertain relationship between content sentiment and engaging in social sharing processes (de Angelis et al. 2012; Hansen et al. 2011). People refrain from sending bad news, to avoid risking negative assessments of their personalities (Rosen and Tesser 1972). Similarly, content with negative sentiment or bad news might be shared less through mechanisms with high self-focus expression. Alternatively, people might share negative content more frequently through such self-focused sharing mechanisms because they seek to enhance their own self-esteem at the expense of others' bad experiences (de Angelis et al. 2012).

To investigate the effects of different sharing mechanism designs, I conducted three empirical studies. First, with a field study, I investigated the effects of different sharing mechanism designs on content sharing. Second, I tested the effects of high control and self-focus expression on users' intentions to share content in a laboratory setting. Third, in another field study, I focused on the effect of the privacy preserving feature on content sharing, using a within-a-single-subject variation. Table 9 provides an overview of the empirical studies.

Study	**Sharing Mechanisms**			**Content Characteristics and Interaction with Sharing Mechanisms**	**User Characteristics and Interaction with Sharing Mechanisms**	**Units of Analysis**	**Advantages**
	Privacy Preserving	High Control	Self-Focus				
Field Study 1	yes	yes	yes	yes	no	Number of shares[5] on Facebook	Cross-media variation
Lab Experiment	no	yes	yes	yes	yes	Intention to share on Facebook	High internal validity
Field Study 2	yes	no	no	no	no	Daily number of shares on Facebook	Single-subject variation

Table 9. Overview of empirical studies

[5] The term „shares on Facebook" combines any recommendations regardless of the underlying sharing mechanism.

3.3 Study 1: Studying Sharing Mechanisms across Different News Media

3.3.1 Data and coding

The data set for Study 1 comes from a large-scale, ongoing project that started in January 2012 to collect data about all articles appearing in the most popular German online newspapers and magazines (Schiller et al. 2016). The web crawlers record each article's title, link to the full text, publication title, and section in which the article was published. The web crawlers visit websites every three hours and capture, for each article, the number of Tweets, Likes, and plus-ones, as well as the publication position for the article (i.e., first page or subpage).

Online Magazines and Newspapers	High User Control	Privacy Preserving	Self-Focus
Bunte.de	Yes	No	No
Chip online	No	No	Yes
FAZ.net	Yes	No	No
Focus Online	Yes	No	No
Handelsblatt.de	No	Yes	Yes
Heise.de	No	Yes	Yes
Spiegel Online	No	No	Yes
Sport1.de	No	Yes	Yes
Stern Online	Yes	No	Yes
Sueddeutsche.de	Yes	No	No
Welt Online	No	No	Yes
Zeit Online	No	Yes	Yes

Table 10. Coding for sharing mechanism implementations (March–September 2012)

From the vast number of articles in the database, I drew a random sample of 4,278 published between March 1 and September 30, 2012 that remained available through permanent links. The main dependent variable is the number of Likes on Facebook, two weeks after its online publication.[6] I also enriched the data set with the variables listed in Table 11. That is, I noted the type of sharing mechanism that the online publication had implemented at the time of analysis (see Table 10) and coded it manually, according to whether it allowed high control over the sharing process, self-focus expression, and privacy preservation. Three outlets implemented a "share" button, six featured a "recommend" button and a caption reading "like" if the user moved the cursor over the button, and one outlet implemented the "like" button. I coded these implementations as self-focus expressions. For the two outlets that implemented both "share" and "recommend" buttons, I coded both sharing mechanisms as providing high control, because users were free to choose which Facebook button to use while visiting the website. The reference category was a single "recommend" button, which neither allowed high control over the sharing process nor expressed a self-focus. With these field data, I also can analyze the effects of privacy

[6] Although each article could be observed for two weeks, I refrain from building panel models, because most of them receive the majority of their Likes on Facebook within six hours of their online publication.

preserving affordances, because four outlets in the data set implemented two-click buttons. Thus, I included a variable to measure this functional affordance.

To control for content characteristics, I followed Berger and Milkman (2012). Using a German automated sentiment analysis dictionary, SentiStrength (Thelwall et al. 2010), I quantified the positivity and emotionality of articles. Positivity refers to the percentage difference in the shares of positive and negative words in an article; emotionality is the percentage of all positive and negative words in the article (Berger and Milkman 2012). I also categorized articles into different topic areas (e.g., science, technology, sports, politics, business, etc.) and used dummy variables to capture their effects.

Next, four coders were engaged to classify the articles further[7]. These coders were not informed about the research question; instead, I provided them with the coding instructions issued by Berger and Milkman (2012) (available at www.marketingpower.com/jmr_webappendix). They rated the articles on the emotional dimensions of anger, awe, sadness, and anxiety, as well as on interest, surprise, and practical utility. They coded the authorship of the articles and indicated the number of accompanying images and videos. Finally, coders rated each article on a five-point Likert scale (Likert 1932) according to the extent to which it evoked certain emotions or might have practical relevance. I trained the coders with a test set of articles to ensure good interrater reliability (pairwise Holsti-Index; Holsti 1969).

Because author characteristics might influence the popularity and likelihood of being shared, especially when famous authors have good fan bases, I controlled for the author's fame, which is calculated by counting the hits on the Bing search engine[8] when her or his name and the keyword "author" is entered. As discussed in Section 2.3.3 women might have different writing styles, so I controlled for author gender; in addition, some authors have complex writing styles that could be cumbersome for readers. Well-written articles are more likely to be read and thus more likely to be shared. To measure writing complexity, the Flesch-Reading-Ease metric was applied, a ubiquitous scale that is even bundled with popular word processing programs and services. Another dummy variable measured whether the article was based on reports from news agencies; such articles may be less likely to be shared, because they offer early versions of common knowledge, so readers may believe others already are aware of the information and refrain from sharing it. Table 12 provides examples of articles that scored highly on these distinct dimensions.

The article features might influence content sharing too. Strufe (2010) finds that profiles with a photo in a business-related social medium are more popular than those without, so I assessed whether the content featured video and images, because it might be more attractive and more shared.

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[7] Many thanks to Daria Hinz, Mahera Najib, Jörg Podesky and Christina Kraus for their invaluable assistance in data coding.

[8] Bing provides an appropriate application programming interface, whereas Google closely limits the number of requests in a certain time period.

Group	Variable	Notation	Source	Description
Sharing mechanism	High control	*High_control*	Manually coded	1 = implements Share button; 0 = otherwise
	Self-focus	*Self_focus*	Manually coded	1 = displays the word "like"; 0 = otherwise
	Privacy preserving feature	*Privacy*	Manually coded	1 = implements two clicks buttons; 0 = otherwise
Content characteristics	Positivity	*Positivity*	Based on the results of SentiStrength analysis	Difference between the percentages of positive and negative words in the article
	Emotionality	*Emotionality*	Based on the results of SentiStrength analysis	Percentage of positive and negative words in the article
	Anger	*Anger*	Manually coded	Likert scale, 1 = "not at all," 5 = "extremely"
	Anxiety	*Anxiety*	Manually coded	Likert scale, 1 = "not at all," 5 = "extremely"
	Awe	*Awe*	Manually coded	Likert scale, 1 = "not at all," 5 = "extremely"
	Sadness	*Sadness*	Manually coded	Likert scale, 1 = "not at all," 5 = "extremely"
	Surprise	*Surprise*	Manually coded	Likert scale, 1 = "not at all," 5 = "extremely"
	Practical utility	*Pract_utility*	Manually coded	Likert scale, 1 = "not at all," 5 = "extremely"
	Interest	*Interest*	Manually coded	Likert scale, 1 = "not at all," 5 = "extremely"
	Section dummies (13)	*D_science etc.*	Captured by web crawler	1 = article appeared in [science] section; 0 = otherwise
	Writing complexity	*Complexity*	Based on Flesch Reading Test (reverse coded)	100 = extremely difficult, 0 = extremely easy to read
Author characteristics	News agency dummy	*D_agency*	Manually coded	1 = agency; 0 = otherwise
	Female first author	*D_AuthFemale*	Manually coded	1 = female; 0 = male
	First author fame	*AuthFame*	Calculated using Bing entering author name plus "author"	Number of search results
Attention Competition	Number of images	*N_images*	Manually coded	Number of images in the article
	Number of videos	*N_videos*	Manually coded	Number of videos in the article
	Article location (first page dummy)	*D_position*	Captured by web crawler	1 = first page; 0 = subpage
	Media reach	*Reach*	Google Search Trends	Weekly search ranking place, reverse coded
	Number of articles published at t	*N_articles*	Calculated from the data set	Number of articles published at the same day
Time effects	Weekend dummy	*D_weekend*	Calculated from the data set	1 = weekend day; 0 = work day
	Time of day dummies (8)	*D_hour00 etc.*	Captured by web crawler	1 = article appeared between [12:00 a.m. and 3:00 a.m.]; 0 = otherwise
	Day t	*t*	Calculated from the data set	Calendar date

Table 11. Variables in Study 1

To control for time and attention competition factors, I determined the number of articles published on the same day. As Rogers (2010) and Berger (2014) notes, a key determinant of the successful diffusion of new products is accessibility. In an online context, content that is prominently positioned is more likely to get popular. According to Tucker and Zhang (2011), such designated information affects consumer choices. I therefore include a variable for where the content appears. Most readers start reading online magazines at the homepage, such that articles published on that start page are more likely to be read and shared on social media. To control for the reach of the online publications, I used the Google search trends ranking as a proxy. Finally, there might be time effects for the general number of shares, so I controlled for the time the article first appeared online. In this case, I created eight dummy variables to divide each weekday into three-hour periods, as well as a dummy variable for a weekend day.

Variable	**German Title and English Translation**
Positivity	*Neues Glück für Michelle Hunziker: Mit Tomaso auf Wolke sieben* New felicity for Michelle Hunziker: with Tomaso on cloud nine
Emotionality	*Macaulay Culkin: Sein Vater fürchtet um sein Leben!* Macaulay Culkin: His father father fears for his life
Anger	*Radsport WM: Deutsche Teamsprinter disqualiziert* Cycling worldcup: German team is disqualied
Anxiety	*Nach Fukushima: Japans Regierung erwägt ersten AKW-Neustart* Japan plans to re-start nuclear power plants
Awe	*Wie Guerilla-Gärtner illegal Städte begrünen* How Guerrilla gardeners plant greenery on cities
Sadness	*Bericht von Unicef: Kindersterblichkeit seit 1990 weltweit halbiert* Unicef report: Child mortality halved since 1990
Surprise	*Forderung nach Abschaffung des Paragrafen 173: Grünen-Politiker Ströbele will Inzest erlauben* German politician Ströbele wants to change law to legalize incest
Practical Utility	*Die zehn schönsten Wanderrouten* 10 most beautiful hiking routes
Interest	*Chinesischer Jugendlicher: Eine Niere im Tausch für ein iPad* Chinese teenager exchanges kidney for an iPad
First Author Fame	*Ein Witz von Guido Knopp* A joke by Guido Knopp
Writing complexity	*EZB-Mitarbeiter fordern Inflationsschutz für Rente* European central bank employees demand protection of retirement pays from inflation
Number of Pictures	*18 deutsche Filme sind in Cannes am Start* 18 German movies are part of Cannes
Number of Videos	*So drücken Sie Ihre Energie-Rechnung* A guide how to lower your energy bill

Table 12. Exemplary articles with high scores on different dimensions

I reasoned that articles that e.g., appeared at 10:00 p.m. draw less attention than articles that appear 10:00 a.m., in line with Szabo and Huberman's (2010) finding that sharing activities differ across distinct time points. Moreover, people might read online articles more often on work days than on weekend. I further use a linear time trend that captures the steady growth of the social medium over time. Table 11 gives an overview of the variables used in Study 1.

Group	Variable	M	SD	Min	Max	Percentage of Sample
Dep. Variable	*N_Likes*	36.19	175.42	0	4424	
Sharing mechanisms	*High_control*	-	-	-	-	47.36
	Self_focus	-	-	-	-	57.81
	Privacy	-	-	-	-	47.99
Content characteristics	*Positivity*[a]	-.15	.89	-15.38	11.11	-
	Emotionality[a]	1.40	2.16	0	38.46	-
	Anger[a]	2.28	1.16	1	5	-
	Anxiety[a]	1.98	1.07	1	5	-
	Awe[a]	1.72	.90	1	5	-
	Sadness[a]	2.04	1.12	1	5	-
	Surprise[a]	2.47	1.02	1	5	-
	Pract_utility[a]	1.77	.96	1	5	-
	Interest[a]	3.02	.92	1	5	-
	D_cars	-	-	-	-	2.73
	D_career	-	-	-	-	.84
	D_society	-	-	-	-	9.91
	D_culture	-	-	-	-	5.80
	D_lifestyle	-	-	-	-	1.89
	D_politics	-	-	-	-	20.57
	D_local	-	-	-	-	1.33
	D_travel	-	-	-	-	1.78
	D_humor	-	-	-	-	.42
	D_sports	-	-	-	-	31.28
	D_technology	-	-	-	-	3.10
	D_business	-	-	-	-	17.13
	D_science	-	-	-	-	2.31
Author characteristics	*D_agency*	-	-	-	-	59.49
	D_AuthFemale	-	-	-	-	11.97
	AuthFame	571.34	1967.93	0	33700	-
	Complexity	67.64	15.37	6	100	-
Attention competition	*N_images*	3.37	9.14	0	222	-
	N_videos	.12	.45	0	9	-
	N_articles	1859.38	336.09	962	2690	-
	D_Position	-	-	-	-	21.30
	Reach					-
Time effects	*D_hour00*	-	-	-	-	7.18
	D_hour03	-	-	-	-	1.57
	D_hour06	-	-	-	-	1.45
	D_hour09	-	-	-	-	8.06
	D_hour12	-	-	-	-	21.55
	D_hour15	-	-	-	-	22.65
	D_hour18	-	-	-	-	23.24
	D_hour21	-	-	-	-	14.31
	D_Weekend	-	-	-	-	20.62
	t			49	260	-

[a] Before standardization.

Table 13. Summary statistics for Study 1

3.3.2 Summary statistics and estimation strategy

Table 13 provides the summary statistics. I estimated the model using negative binomial regression, because (1) the dependent variable can take on discrete, non-negative values and (2) its variance exceeds the mean (overdispersion)[9]. The estimation equation is:

$$Prob(N\_Likes = N\_Likes_i|\boldsymbol{x}_i) = \frac{e^{-\lambda_i}\lambda_i^{N\_Likes_i}}{N\_Likes_i!} \text{ with } \lambda_i = e^{x_i'\boldsymbol{\beta}+\varepsilon},$$

where N_Likes_i indicates the number of shares of article i , and $\boldsymbol{x}_i$ is a vector describing article i on the different dimensions. A gamma-distributed error ε with unity mean and variance α accommodates the overdisperson of the dependent variable (Kennedy 2003). I used robust standard errors to account for heteroscedasticity in the data set.

3.3.3 Results and discussion

The random sample of 4,278 articles produced the results in Table 14 (see Model 7). The Wald tests of all models showed that at least one regressor was not equal to 0 ($p < .001$). The likelihood ratio test of the overdispersion parameter strongly suggested it was non-zero ($p < .001$), and the negative binomial model was preferable to the Poisson model for the data set.

The sharing mechanisms that allow high control over the sharing process ($p < .05$) and self-focus expression ($p < .01$) negatively affected content sharing. Specifically, online publications that implement a sharing mechanism that allows for high control over the sharing process should expect an incidence rate ratio (IRR) of content shared on Facebook that is 36% lower, *ceteris paribus*, than it would be for mechanisms with restricted control. Sharing mechanisms that express a self-focus also decrease the IRR of articles shared on Facebook by 44%, with all other variables in the model constant. Furthermore, online newspapers and magazines suffer when they launch two-click buttons to preserve users' privacy: The IRR for articles published with two-click sharing mechanisms was 49% lower than for those without the mechanisms ($p < .001$).

With respect to content characteristics, I found an insignificant effect of positively written articles, as well as an insignificant interaction effect between positivity and sharing mechanisms with self-focus expression. However, emotionality ($p < .001$) related negatively to content sharing, such that a one standard deviation increase in emotionality lowered an article's IRR by 26%, with all other variables held constant. This finding is in sharp contrast with Berger and Milkman's (2012) findings, which might be caused by cultural differences or suggest a preference for good journalism, which aims for objectivity, neutrality, and fact verification (Tsfati et al. 2006), such that readers would not value emotional articles.

[9] I also estimated the model using zero-inflated negative binomial regression, because 33% of the articles in the sample had zero shares. The Vuong test showed no significant differences between the negative binomial regression and the zero-inflated model.

Variable	(1) *N Likes*	(2) *N Likes*	(3) *N Likes*	(4) *N Likes*	(5) *N Likes*	(6) *N Likes*	(7) *N Likes*	(7) IRR
High_control	-1.349***	-1.090***	-1.047***	-0.901***	-0.777***	-0.720***	-0.439*	0.64*
	(-7.65)	(-6.07)	(-6.06)	(-4.51)	(-3.82)	(-3.43)	(-1.97)	
Self_focus	-1.212***	-1.087***	-1.039***	-1.155***	-0.889***	-0.817***	-0.584**	0.56**
	(-5.99)	(-5.40)	(-5.11)	(-5.49)	(-3.92)	(-3.51)	(-2.59)	
Privacy	-0.540**	-0.518**	-0.492**	-0.792***	-0.904***	-0.882***	-0.676***	0.51***
	(-3.16)	(-3.14)	(-2.88)	(-5.78)	(-7.00)	(-6.74)	(-5.70)	
Positivity[a]		0.012	0.025	0.129^{+}	0.125	0.133^{+}	0.120	1.13
		(0.18)	(0.38)	(1.66)	(1.57)	(1.68)	(1.63)	
Emotionality[a]		-0.407***	-0.357***	-0.365***	-0.286***	-0.303***	-0.306***	0.74***
		(-5.53)	(-4.93)	(-6.10)	(-5.07)	(-5.05)	(-5.00)	
*Self_focus*positivity*[a]		0.016	0.045	-0.055	-0.078	-0.086	-0.061	0.94
		(0.18)	(0.53)	(-0.53)	(-0.77)	(-0.83)	(-0.66)	
Anger[a]			0.303***	0.308***	0.321***	0.318***	0.343***	1.41***
			(4.14)	(4.97)	(5.26)	(5.31)	(6.10)	
Awe[a]			0.084	0.156*	0.136*	0.130^{+}	0.164**	1.18**
			(1.24)	(2.22)	(2.04)	(1.93)	(2.67)	
Sadness[a]			-0.127^{+}	-0.087	0.006	0.009	-0.041	0.96
			(-1.91)	(-1.15)	(0.07)	(0.10)	(-0.68)	
Anxiety[a]			-0.020	-0.027	-0.056	-0.052	-0.085	0.92
			(-0.28)	(-0.37)	(-0.81)	(-0.74)	(-1.39)	
Interest[a]			0.170*	0.239***	0.191**	0.200***	0.200***	1.22***
			(2.53)	(4.11)	(3.19)	(3.35)	(3.78)	
Surprise[a]			0.004	-0.026	0.050	0.053	0.063	1.06
			(0.05)	(-0.38)	(0.83)	(0.88)	(1.14)	
Pract_utility[a]			-0.0708	-0.189***	-0.181**	-0.185**	-0.153**	0.86**
			(-1.20)	(-3.44)	(-3.15)	(-3.19)	(-2.85)	
Section dummies (12)				Yes	Yes	Yes	Yes	-
D_agency					-0.980***	-0.942***	-0.968***	0.38***
					(-7.19)	(-6.86)	(-7.30)	
D_AuthFemale					-0.032	-0.010	0.035	1.04
					(-0.17)	(-0.05)	(0.19)	
AuthFame					7.78e-5**	8.20e-5**	6.04e-5*	1.00*
					(2.63)	(2.81)	(2.57)	
Complexity					-0.016***	-0.016***	-0.014***	0.99***
					(-3.93)	(-3.93)	(-3.81)	
N_images						0.016*	0.014*	1.01*
						(2.31)	(2.31)	
N_videos						0.029	-0.032	0.97
						(0.24)	(-0.29)	
D_Position							0.457**	1.58**
							(3.18)	
N_articles							-8.39e-4*	1.00*
							(-2.41)	
Reach							-3.26e-3	1.00
							(-1.09)	
t							8.90e-4	1.00
							(1.15)	
Time of day dummies							Yes	-
D_weekend							-0.499^{+}	0.61^{+}
							(-1.85)	
Constant	5.123***	4.832***	4.713***	5.299***	6.431***	6.269***	7.080***	-
	(21.03)	(19.52)	(19.54)	(13.20)	(12.55)	(11.75)	(7.66)	
Ln alpha	1.659***	1.627***	1.603***	1.466***	1.390***	1.387***	1.353***	1.353***
	(57.76)	(54.33)	(49.94)	(47.83)	(43.43)	(42.73)	(45.12)	(45.12)
Pseudo R^2	0.003	0.008	0.011	0.031	0.041	0.042	0.046	0.046
Log likelihood (full model)	-14954.9	-14886.7	-14836.6	-14547.9	-14387.7	-14381.6	-14311.4	-14311.4
Log likelihood (constant only)	-15006.4	-15006.4	-15006.4	-15006.4	-15006.4	-15006.4	-15006.4	-15006.4
Wald χ^2-Test	62.63***	123.4***	155.8***	433.3***	688.7***	701.3***	965.4***	965.4***

Notes: N = 4,278, *t* statistics in parentheses. $^{+}$ $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$. [a] Standardized values.

Table 14. Estimation results: Effect of sharing mechanism design on content sharing

In line with Berger and Milkman (2012), anger ($p < .001$), awe ($p < .01$), and interest ($p < .001$) offered good predictors of content virality. Content that evokes anxiety, sadness, or surprise instead had insignificant effects. Furthermore, in contrast with Berger and Milkman (2012), I do find that Facebook users avoided sharing articles that offered practical utility ($p < .01$). This finding resonates with Schulze et al.'s (2014) assertion that Facebook is poorly suited for broadcasting utilitarian products.

The Facebook users in the sample shared complex articles more frequently ($p < .001$), and the first author's fame and article location on the website both were strong, positive predictors of content sharing. The number of images used in the article related positively to sharing probability on Facebook ($p < .05$). Finally, if news agencies were the sources of the information, articles were less frequently shared ($p < .001$), as I hypothesized.

3.4 Study 2: Laboratory Experiment, Effects of High User Control and Self-Focus Expression

3.4.1 Experimental design

I conducted a computer-assisted laboratory experiment to study the causal effects of self-focus expression and high user control through Facebook's sharing mechanisms on content-sharing behavior. I used real implementations of Facebook's sharing mechanisms, namely, a Share and two versions of the Like button. Each participant read eight press articles and decided how likely he or she was to share/like/recommend them on Facebook (seven-point Likert-scale, 7 = "very likely," 1 = "not at all likely"). The questionnaire asked about users' demographic and personal traits, general reading interests, and Facebook usage habits. I varied the design of the different sharing mechanisms between-subjects and content characteristics within-subjects.

With regard to the sharing mechanisms, each participant was assigned randomly to one of the three conditions and thus interacted with sharing mechanisms that varied in the level of control they granted to the user and the symbolic expression of self-focus (see Table 15). I explained the functionality of the sharing mechanism assigned to each group. I also adapted the wording of the tasks to match each condition and displayed the relevant Facebook button below each article.

Sharing Mechanism	High Control	Self-Focus
"Share"	Yes	No
"Like"	No	Yes
"Recommend"	No	No

Table 15. Sharing mechanisms variation between groups

Because sentiment and other content characteristics affect the likelihood of sharing that content (Berger and Milkman 2012), I chose the articles for this experiment carefully. This selection process was challenging, because I needed current articles that fulfilled multiple other conditions. Because I am primarily interested in the interaction between content sentiment and self-focus expression, I sought articles with different sentiment levels (positive, negative, and neutral). Again using the SentiStrength dictionary (Thelwall et al. 2010), I quantified the positivity, or the percentage difference between the shares of positive and negative words in the article (Berger and Milkman 2012), of 3,104 articles published by the leading German news outlet *Spiegel Online* between December 1, 2013, and February 3, 2014. Next, I excluded outdated articles, blogs, and image and video reports. Thematically, the articles pertained to the science, lifestyle, culture, and travel categories.[10] The eight selected articles were comparable in their length and writing complexity, according to the Flesh-Index for German (the free online tool is available at http://www.leichtlesbar.ch/html/_ergebnis.html).

[10] Study 1 indicated that articles related to these topics were equally likely to be shared through social media.

Article	**Interest**	**Practical utility**	**Surprise**	**Anger**	**Awe**	**Sadness**	**Anxiety**	**Complexity**	**Words**	**Positivity**	**Emotionality**
1	4.66	4	2.66	1.66	1.33	1.33	2	28	369	-0.54	1.63
2	4.66	3.33	4	1	1	1	1.66	47	747	-0.13	0.67
3	5	3.66	3.33	1	1.33	1.33	1	38	753	0.27	0.53
4	4.33	1.33	3.66	1	1.33	1	1	42	774	-0.26	0.78
5	3.66	1.33	3.33	1	1.66	1.33	1	32	815	0.00	0.49
6	3.33	1	3.66	2.33	3.33	1.66	1	23	828	0.00	0.48
7	2.66	2	3.33	1.66	3.33	2.33	1	39	870	0.00	0.69
8	4.66	2.33	3.33	1	2	1	1	37	894	0.11	0.34
M	4.17	2.67	3.38	1.63	2.09	1.63	1.50	35.75	753.88	-0.05	0.69
SD	0.72	1.22	0.49	0.72	0.92	0.49	0.76	7.25	153.57	0.24	0.38
Cronbach's alpha	0.75	0.77	0.63	0.62	0.55	0.66	0.63	-	-	-	-

Table 16. Online articles used in the experiment

To exclude potential bias, I characterized online articles according to the dimensions that Berger and Milkman (2012) identify as content virality drivers. Specifically, I calculated articles' emotionality, as the percentage of positive and negative words in the article (Berger and Milkman 2012), then engaged three human coders to classify the articles on further dimensions. Following the same coding directions as in Study 1 (see Berger and Milkman (2012), available at www.marketingpower.com/jmr_webappendix), the coders were not informed about the research question but rated the articles on the four emotional dimensions and on their interest, surprise, and practical utility, using a five-point Likert (Likert 1932) scale. The interrater reliability, measured by Cronbach's α (Cronbach 1951), was acceptable for each dimension (.77 > α > .62) except awe (α = .55; Table 16). The articles were similar on some dimensions (e.g., sadness, anxiety) but varied on others (e.g., practical utility). Table 16 contains description of the articles along the emotional dimensions. In addition to images accompanying the articles, I removed information about the author and magazine to avoid a potential bias.

Users' personal traits and characteristics account for their varying engagement in social sharing processes (Hennig-Thurau et al. 2004; Ho and Dempsey 2010; Phelps et al. 2004). Following previous research, I control for three personal traits: motivation to be part of a group (need to belong), altruism, and extraversion (see Table 17). I also considered demographics (gender, age, and education level), general reading interest, and Facebook usage habits (number of friends, frequency of content sharing). To measure the psychographic variables need to belong, altruism, and extraversion, I used scales from previous research (Table 16). For the measure of Facebook use, I relied on interval variables.

Variable	Measure	Source	Cronbach's α
Need to belong	10-item, seven-point Likert scale	(Leary et al. 2013)	.70
Altruism	10-item, seven-point Likert scale	NEO-FFI (Costa and McCrae 1992)	.87
Extraversion	9-item, seven-point Likert scale	NEO-FFI (Costa and McCrae 1992)	.80

Table 17. Measures of users' personal traits

3.4.2 Participants, summary statistics, and estimation approach

I did not inform the participants of the research question; instead, I simply revealed that the study sought to investigate what content generally gets shared on social media. As an incentive, each participant received 5€ for participating and was entered into a raffle for three 50€ Amazon vouchers. I conducted the experiment during February 17–March 13, 2014, and each session took approximately 20–30 minutes. A valid Facebook account was required to participate; the 124 Facebook users whom the research assistants recruited on the university campus were randomly assigned to the three conditions: "share" button (n = 43), "like" button (n = 42), and "recommend" button (n = 39).

Table 18 details the sample's characteristics. Both genders were equally represented; users with high school degrees predominated. With respect to users' activity on Facebook, I find a normal distribution in the number of friends, but sharing activity exhibited a right-skewed distribution, such that 38% of participants shared content occasionally, 2% did so once a day, and 2% several times a day. The mean age was 22 years. Users appeared generally more interested in articles related to science, technology, travel, politics, sports, and humor. The χ^2 tests showed that, with regard to personal traits, demographics, and Facebook usage habits, users were randomly assigned to the treatment groups.

Because the dependent variable requires a seven-point Likert scale, I applied an ordered logistic regression to estimate the effects of different sharing mechanism designs—namely, high control over the sharing process and self-focus—on users' intentions to share online content. To enhance the interpretation of the estimation results, I standardized the variables that measured positivity, emotionality, anger, awe, sadness, anxiety, interest, practical utility, and surprise. I also included the interaction effects of the self-focus expression with positivity and extraversion.

The estimation equation thus read:

$$Pr(IntLike_{ij} = 1) = \Lambda(-(\boldsymbol{x}'\beta + \varepsilon_{ij}))$$
$$Pr(IntLike_{ij} = m) = 1 - \Lambda(\mu_{m-1} - (\boldsymbol{x}'\beta + \varepsilon_{ij})) \text{ for } m \in (1;7]$$

where $IntLike_{ij}$ measures user j's intention to share an article i. The vector $\boldsymbol{x}$ describes article i on several content-related and user j–related characteristics. The μ values represent the thresholds for the user's latent intention to share an article. $\Lambda(.)$ denotes the logistic cumulative distribution function.

Variable	Categories	Notation	Percentage of sample	M	SD	Min	Max
Age	-	*Age*	-	22.09	3.39	15	33
Need to belong	-	*Need_to_belong*	-	4.46	.86	1.1	6.3
Extraversion	-	*Extraversion*	-	4.90	1.03	1.89	6.89
Altruism	-	*Altruism*	-	5.95	.65	3.3	7
Gender	Female	*Female*	51.61	-	-	-	-
	Male	-	48.39	-	-	-	-
Education Level	High school	*D_highschool*	66.94	-	-	-	-
	Bachelor	*D_bachelor*	21.77	-	-	-	-
	Master	*D_master*	11.29	-	-	-	-
	Phd	*D_phd*	0	-	-	-	-
Number of friends	1-100	*D_friends100*	11.29	-	-	-	-
	101-200	*D_friends200*	27.42	-	-	-	-
	201-300	*D_friends300*	23.39	-	-	-	-
	301-400	*D_friends400*	17.74	-	-	-	-
	401-500	*D_friends500*	6.45	-	-	-	-
	More than 500	*D_friendsmore500*	13.71	-	-	-	-
Frequency of sharing on Facebook	Never	*D_never*	8.87	-	-	-	-
	As good as never	*D_as_good_as_never*	37.90	-	-	-	-
	Once a month	*D_once_month*	17.74	-	-	-	-
	Once a week	*D_once_week*	15.32	-	-	-	-
	Several times a week	*D_several_week*	16.13	-	-	-	-
	Once a day	*D_once_day*	1.61	-	-	-	-
	Several times a day	*D_several_day*	2.42	-	-	-	-
User's reading interests	Cars	*D_cars*	15.32	-	-	-	-
	Career	*D_career*	42.74	-	-	-	-
	Society	*D_society*	38.71	-	-	-	-
	Humor	*D_humor*	63.71	-	-	-	-
	Culture	*D_culture*	41.94	-	-	-	-
	Sports	*D_sports*	49.19	-	-	-	-
	Lifestyle	*D_lifestyle*	25.81	-	-	-	-
	Local news	*D_localnews*	19.35	-	-	-	-
	Politics	*D_politics*	45.16	-	-	-	-
	Travel	*D_travel*	54.84	-	-	-	-
	Technology	*D_technology*	48.39	-	-	-	-
	Business	*D_business*	29.03	-	-	-	-
	Science	*D_science*	69.35	-	-	-	-

Table 18. Sample characteristics

3.4.3 Results and discussion

Table 19 contains the results of the ordered logistic estimation. The Wald tests in all models indicated that at least one of the independent variables was not zero ($p < .001$). First, the effect of high control was negative ($p < .01$) and robust, regardless of the model specification. If a content provider implemented a sharing mechanism that allowed users to exert high control over the sharing process (e.g., "share" button), the odds ratio (OR) for sharing the content was 44% lower than for the sharing mechanisms with low control, given that the other variables in the model remained constant. These sharing mechanisms apparently required sufficiently high effort that users became less willing to share the content with their peers. Second, the effect of the self-focus expression was highly significant ($p < .01$) and negative but not robust across the different model specifications. Its effect was significant when I controlled for users' extraversion and its interaction with a self-focus expression. The general effect of a self-focus expression was negative, so users who were not extroverted refrained from sharing content when the sharing mechanisms exhibited this symbolic expression. The odds pertaining to a user's willingness to share fell 88%, ceteris paribus, compared with those for mechanisms expressing other-focus. However, its interaction with a user's extraversion revealed a positive effect ($p < .001$), such that extroverted persons used these mechanisms to give voice to their feelings and opinions. The mechanism expressing self-focus increased the odds of content being shared by extroverted persons, ceteris paribus, by 57%. No other personal traits had significant effects on willingness to share online articles.

I controlled for the content virality drivers identified by Berger and Milkman (2012). In contrast with their results, the effects of content positivity ($p < .001$) and emotionality ($p < .001$) were negative. Similar to the findings from Study 1, the interaction of self-focus expression and content sentiment was negative but insignificant.[11]

Finally, older people appeared rather reluctant to share content through social media ($p < .001$), such that these odds decreased by 16%, with other variables held constant. I found no difference in sharing behavior between genders, but higher levels of education increased willingness to share content ($p < .001$). Counterintuitively, the more Facebook friends a user had, the more reluctant he or she was to share content on Facebook ($p < .001$), perhaps because users with many friends lose track of who might be interested in any particular content. The effect of regular sharing behavior on Facebook was positive, as I expected.

[11] I could not find articles that were identical on all dimensions, so I controlled for other content characteristics (e.g., evoking different emotions, interest, practical utility), but I recommend caution in interpreting these findings, because of the small sample size of articles in the laboratory experiment.

Variable	(1) *IntLike*	(2) *IntLike*	(3) *IntLike*	(4) *IntLike*	(5) *IntLike*	(6) *IntLike*	(6) OR
High_control	-0.792***	-0.809***	-0.846***	-0.784***	-0.734***	-0.588**	0.56**
	(-5.55)	(-5.63)	(-5.88)	(-4.64)	(-4.24)	(-2.90)	
Self_focus	-0.088	-0.070	-0.066	0.007	-1.354*	-2.093**	0.12***
	(-0.64)	(-0.50)	(-0.47)	(0.05)	(-2.17)	(-3.12)	
Positivity[a]		-0.030	-3.965**	-4.290***	-4.284***	-4.433***	0.01***
		(-0.23)	(-3.27)	(-3.45)	(-3.43)	(-3.53)	
Emotionality[a]		0.313**	-4.697***	-5.074***	-5.073***	-5.239***	0.01***
		(2.59)	(-3.45)	(-3.63)	(-3.62)	(-3.71)	
Self_focus Positivity*[a]		-0.088	-0.090	-0.085	-0.083	-0.065	0.94
		(-0.76)	(-0.75)	(-0.71)	(-0.69)	(-0.54)	
Content Characteristics (7)			Yes	Yes	Yes	Yes	Yes
Age				-0.159***	-0.177***	-0.178***	0.84***
				(-4.71)	(-5.02)	(-4.64)	
Female				-0.093	-0.028	0.203	1.23
				(-0.67)	(-0.19)	(1.03)	
Education level dummies (4)				Yes	Yes	Yes	-
Number of friends dummies (6)				Yes	Yes	Yes	-
Facebook use dummies (7)				Yes	Yes	Yes	-
Need_to_belong					0.024	0.070	1.07
					(0.29)	(0.78)	
Altruism					-0.195	0.0122	1.02
					(-1.54)	(0.09)	
Extraversion					0.111	0.037	1.01
					(1.15)	(0.36)	
Self_focus Extraversion*					0.294*	0.453***	1.57***
					(2.35)	(3.29)	
Reading interests dummies (13)						Yes	-
Pseudo R^2	0.011	0.025	0.045	0.076	0.080	0.097	0.097
Log Likelihood (full model)	-1692.2	-1669.0	-1634.8	-1581.6	-1575.0	-1544.6	-1544.6
Log Likelihood (constant only)	-1711.2	-1711.2	-1711.2	-1711.2	-1711.2	-1711.2	-1711.2
Wald χ^2 Test	36.62***	83.21***	138.3***	249.1***	268.1***	315.4***	315.4***

Notes: N = 992. *t* statistics in parentheses. $^+$ $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$. [a] Standardized variables

Table 19. Effects of sharing mechanism design on intentions to share an article on Facebook

3.5 Study 3: Effects of Privacy Preserving Features in a Single-Subject Variation

3.5.1 Data and estimation strategy

With the third study, I analyzed the effects of a privacy preserving feature in a single-subject variation setting. In response to the privacy debates in 2011 in Germany (Zota 2014), a popular tabloid, BILD.de, introduced two-click buttons on its website during the 50th week of 2012, then abolished them nearly a year later, in the 47th week of 2013. The resulting data set offers natural variation within a single subject. The data again came from the ongoing project to monitor Germany's top online newspapers and magazines. For Study 3, these data consisted of 78,060 articles published between February 1, 2012, and December 31, 2013. I could not conduct content or sentiment analyses, because BILD.de does not create permanent links, and older articles become unavailable online. Therefore, I aggregated the number of Facebook shares on a daily basis and excluded December 28, 2013, because the web crawlers suffered some technical problems on that date. The final data set contained 699 observations of aggregated shares (N_Likes) on Facebook.

On December 5, 2013, BILD.de also introduced a paywall, which restricted access to some content to paying members. The paywall might limit the number of users and thus the number of shares (Oh et al. 2016), so I controlled for its effect with a dummy variable. I also controlled for time effects with a weekend dummy variable, because people tend to read online newspapers less on weekends. Further, I control for the general time trend and include month dummies to capture seasonal effects, because during summer months, people often take holidays or enjoy good weather, which might reduce the time they spend online. Figure 8 details these seasonal movements.

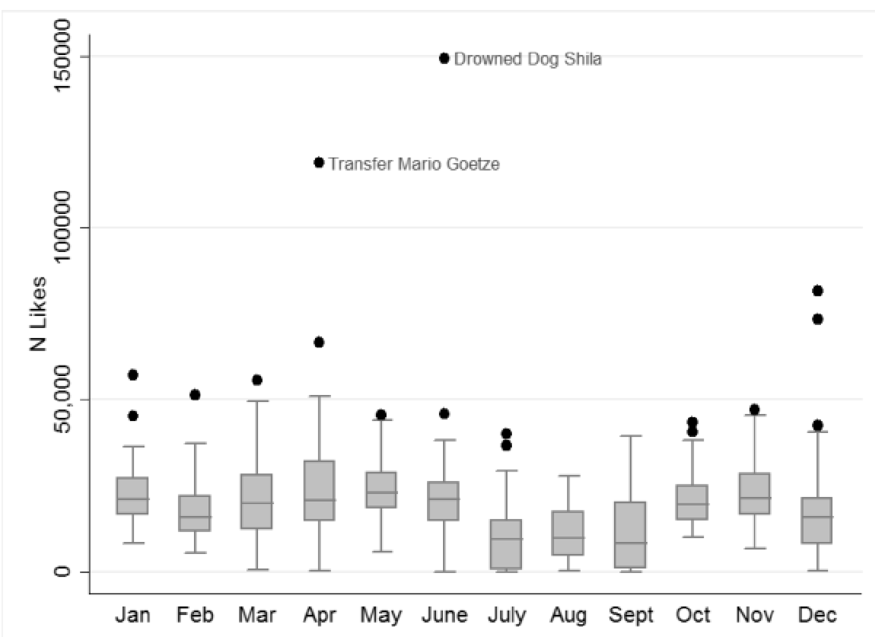

Figure 8. Seasonal fluctuation of Facebook shares per day

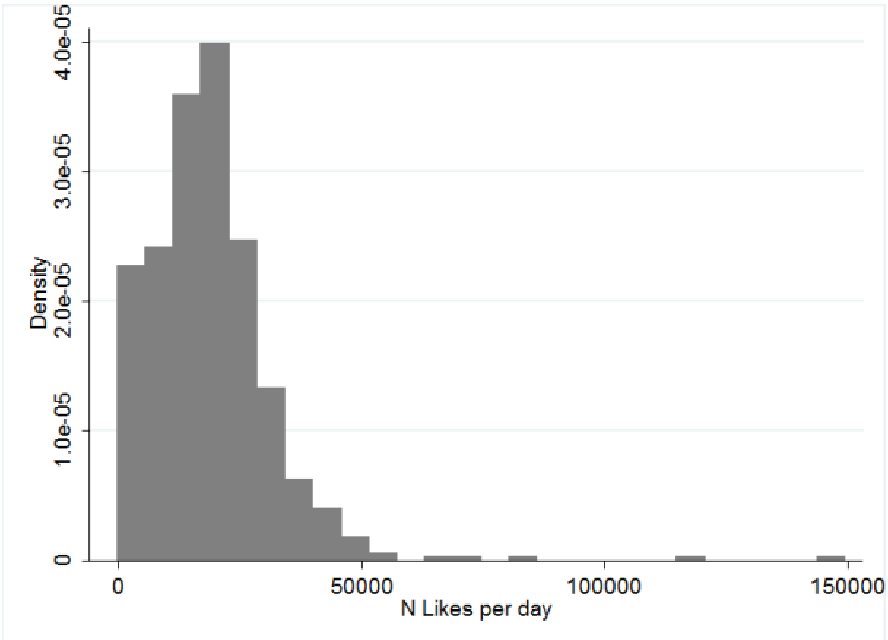

Figure 9. Distribution of number of Facebook shares per day

Figure 9 depicts the distribution of aggregated Likes on Facebook. Two outliers emerged from the data set: (1) an article reporting the trade of the soccer player Mario Goetze to Bayern Munich (April 2013, 68,801 Likes) and (2) an article about a drowned dog (June 2013, 62,229 Likes). Table 20 provides some sample summary statistics.

The count characteristics of the data and the overdispersion of the dependent variable prompted me again to estimate an equation using negative binomial regression with robust standard errors, as follows:

$$Prob(N\_Likes = N\_Likes_t | \boldsymbol{x}_t) = \frac{e^{-\lambda_i}\lambda_t^{N\_Likes_t}}{N\_Likes_t!} \text{ with } \lambda_t = e^{x_t'\boldsymbol{\beta}+\varepsilon},$$

where N_Likes_t measures the number of aggregated recommendations on day t, and $\boldsymbol{x}_t$ is the vector describing the set of articles on day t across different dimensions. A gamma-distributed error ε with unity mean and variance α accommodates the overdisperson of the dependent variable (Kennedy 2003). I used robust standard errors to account for heteroscedasticity.

3.5.2 Results and discussion

I provide the estimation results in Table 21. The likelihood ratio test of the parameter alpha that accommodates overdispersion in the data was highly significant, confirming the appropriateness of the negative binomial regression rather than a Poisson model. The Wald χ^2 test revealed that at least one of the independent variables explained variation in the dependent variable ($p < .001$). The constant term indicated the expected number of Likes on Facebook of a set of articles published on a work day in January, with the one-click design and without the paywall: exp10.27 = 28,853.89 Likes on Facebook.

Variable	Description	Notation	Percentage of Sample	M	SD	Min	Max
N_Likes	Aggregated number of Facebook shares of all articles published on day t	*N_Likes*	-	18749.33	13085.2	0	149409
Privacy	1 = implements two-click buttons; 0 = otherwise	*Privacy*	49.21	-	-	-	-
Paywall	1 = implements paywall; 0 = otherwise	*D_Paywall*	3.58	-	-	-	-
Weekend	1 = weekend day; 0 = otherwise	*D_weekend*	28.47	-	-	-	-
Day t	Calendar date	*t*	-	-	-	20	719
Month	Indicator variable for calendar month						
	January	*D_Jan*	4.43	-	-	-	-
	February	*D_Feb*	8.15	-	-	-	-
	March	*D_Mar*	8.87	-	-	-	-
	April	*D_Apr*	8.58	-	-	-	-
	May	*D_May*	8.87	-	-	-	-
	June	*D_June*	8.58	-	-	-	-
	July	*D_July*	8.87	-	-	-	-
	August	*D_Aug*	8.87	-	-	-	-
	September	*D_Sept*	8.58	-	-	-	-
	October	*D_Oct*	8.87	-	-	-	-
	November	*D_Nov*	8.58	-	-	-	-
	December	*D_Dec*	8.73	-	-	-	-

Table 20. Variable descriptions and summary statistics

Variable	*N_Likes*	IRR
Privacy	-0.349^{*}	0.71
	(-2.39)	
D_Paywall	-0.901^{**}	0.41
	(-2.65)	
D_weekend	-0.241^{***}	0.79
	(-3.86)	
t	5.14e-4	1.00
	(1.25)	
Month dummies	Yes	-
Constant	10.27^{***}	-
	(108.11)	
Ln alpha	-0.276^{***}	-0.276^{***}
	(-3.41)	(-3.41)
N	699	
Pseudo R^2	0.007	
Wald χ^2 tests	176.64^{***}	

Notes: *t* statistics in parentheses
$^{+}$ $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 21. Effects of privacy preserving feature on content sharing

The results confirmed the negative effect of a privacy preserving feature on the number of daily Likes on Facebook ($p < .05$). Ceteris paribus, the newspaper attracted an average of 29% fewer Likes every day when it implemented the two-click design. Thus, our within-subject data set affirmed that two-click buttons limit users from sharing content on Facebook. Because online publications prefer to increase their reach throughout social media, BILD.de has abolished this feature in December 2013.

As expected, the paywall negatively affected the log number of shares ($p < .01$). The IRR of shares on Facebook decreased by 59%, holding all other variables in the model constant. The effect of the paywall was stronger than that of the introduction of privacy preserving sharing mechanisms. However, whereas the newly generated revenues from the paywall helped compensate for this loss of Likes, no such effect mitigated the damage due to the implementation of the two-click design. Finally, articles published on weekends generated 21% fewer Likes on social media ($p < .01$), with the other variables held constant. The general time trend was insignificant.

3.6 General Discussion

In this research project, I analyze sharing mechanisms according to whether they allow high control over the sharing process and offer privacy preserving features (functional affordances), as well as with respect to their self-focus (symbolic expression). I investigated Facebook's social plugins and their impact on the diffusion of German online press articles to analyze how the sharing mechanism design affects content sharing in social media, across two field studies and a laboratory experiment. Sharing mechanisms that allowed high control over the sharing process lowered the likelihood of content sharing through those mechanisms by up to 44%. Furthermore, the two field studies revealed that if content providers implemented mechanisms intended to preserve users' privacy (e.g., two-click designs), the likelihood of content sharing decreased by up to 49%. Even the different symbolic expressions of sharing mechanisms affected users' sharing behavior. Sharing mechanisms that express self-focus decrease sharing likelihood on social media by up to 88%. In contrast with the hypothesis, I found no interaction effect between the content's valence and the symbolic expression of self-focus, though the laboratory experiment indicated that extroverted people make particular use of this feature to vent their feelings, preferences, and opinions.

The findings offer thus several useful suggestions for media industries. Practitioners should implement sharing mechanisms that provide only limited control over the sharing process and do not express self-focus. In this study setting, Facebook's "Recommend" button is the most appropriate sharing mechanism, because it is simple to use and remains neutral. Although I found a positive interaction effect of self-focus with extraversion, I do not suggest implementing the "like" button, because it is impossible to identify extroverted users in advance. Two field studies also offer empirical confirmation of what some business practitioners have long suspected, namely, that the privacy preserving feature negatively affects content-sharing behaviors. I predict that high control and privacy preservation demand greater effort from users, resulting in fewer shares. The main lesson for practitioners is to keep the process as lean and simple as possible. To address users' privacy concerns, social media and content aggregators might need to devise new social plugins that maintain low user effort requirements but still respect users' privacy.

These studies have several limitations that might be addressed by further research. First, I focus mainly on the effects of sharing mechanism designs on content-sharing outcomes, not on which user behaviors they trigger. Additional studies could concentrate on the effects that different sharing mechanisms induce and investigate which effects account best for distinct content-sharing outcomes.

Second, these studies cite Facebook's sharing mechanisms, and some unobserved factors related to Facebook as a social medium might affect the content-sharing outcomes (e.g., users' negative or fun attitudes toward Facebook, Schulze et al. (2014)). Some segments within the user population also might exhibit radically different sharing patterns. Because other social media do not provide different social plugins, it would be possible to conduct laboratory experiments with fictional social media to test for the generalizability of the findings.

4 WHY DISCUSSION BOARDS SERVE AS SPEAKERS' CORNER AND FACEBOOK AS THE NEW DINNER TABLE

4.1 Introduction

This study investigates how the anonymity and content's controversy influence social sharing behavior. As discussed in Section 2.7.5, sharing mechanisms with identity revealing policy might not always facilitate social sharing. For this purpose, I compare social sharing processes in two online communication media on the most popular German online magazine *Spiegel Online* – discussion boards and Facebook. The main difference between these groups is that in the discussion boards the users do not use (or use very rarely) their real names so that the social sharing processes take place under a rather anonymous setting. In contrast, when the users share and comment some content on Facebook, they are no more anonymous (even in case of highly restricted public visibility of their profiles or using pseudonyms, at least close friends know who is behind the focal profile). Conventional wisdom suggests that topics related to politics, sexual life, money and religion are less appropriate for small talks. Does social media which disclose identities of the conversation partners facilitate mainstream topics that are appropriate for a discussion on a dinner table ("weather, kids, and pets")? And do communication tools which allow the users to interact in an anonymous setting contribute to the democratic tradition in terms of serving as a speakers' corner where the users can use the right of freedom of speech and can give voice to their opinions without being punished for a minority opinion on controversial issues?

In the following, I develop the hypotheses of this study. Then I describe the data used and present the descriptive statistics and results of a regression analysis. The study concludes with the summary and a short discussion of the findings.

4.2 Hypotheses Development

Controversial topics are positively related to the likelihood being shared through increased interest (Chen and Berger 2013). At the same time, while talking about controversial content people might feel very uncomfortable. This occurs when conversation partners hold opposing attitudes. Generally, people strive to be liked by others and to conform to social norms. Especially, in social media people have many "friends" that comprise close friends, family members, acquaintances, colleagues and even people who they never met in real life. Because of this heterogeneity, people have less control what happens to their posts on social media. Therefore, with increasing controversy sender's perceived discomfort might increase. Therefore, the hypothesis is as follows:

Hypothesis 1: *The relationship between controversy and the social sharing activities follow an inverted U-shape pattern.*

As discussed in Section 2.7.5, anonymity has positive and negative effects on human behavior. People behave often in negative manner if they are not observed (Christopherson 2007;

Davenport 2002; Moore et al. 2012). In contrast, anonymity also encourages discussion of "difficult" topics in medicine (Makoul et al. 2010) or is associated with privacy and psychological well-being (Bernstein et al. 2011; Christopherson 2007). Although previous research shows that under identity disclosure setting, the outcomes of human behavior are more favorable for the welfare, like fair allocation of resources and donating more money for fund-raising campaigns, I hypothesize that social sharing is affected in such a way that controversial topics are threatened to be lost in the spiral of silence (Noelle-Neumann 1974). The next hypothesis is as follows:

Hypothesis 2: *Controversial content is rather shared using sharing mechanisms that support anonymity.*

In contrast to Chen and Berger (2013), who focus on the psychological process of social sharing, I examine the type of content that is discussed on Facebook and discussion boards.

4.3 Data and Methodology

4.3.1 Data

For the analysis of senders' social sharing activities under different conditions of identity disclosure, I analyze data from *Spiegel Online*, the most popular German online magazine using proprietary software[12]. The data on sharing activities on Facebook comes again from the large still-ongoing project (Schiller et al. 2016). For each article published between November 1st and December 28th 2013 the number of Likes on Facebook and number of comments on the *Spiegel Online*' s discussion board were collected two weeks after publishing. Users on the discussion board of *Spiegel Online* can use pseudonyms for their profiles, so that I assume that social sharing takes place under anonymity condition.

Overall, the data set amounts to 3,740 articles. For the analysis I excluded pictures without text (like "Picture of the day") or series of pictures, video contributions, content related to jokes and comics and articles which were no more available for further textual analysis, like live streams and live tickers. Further, I analyze only content that made it to the top most-read ranking list. As discussed in Section 2.6.2, interest moderates social sharing processes. To eliminate the influence of this variable, I assume that all articles which made it to the top-read ranking are somewhat equal in their interest level. Thus, the final data set contains 1,150 articles.

4.3.2 Measurement of controversy

As discussed in Section 2.6, controversy is a construct that is not easy to measure. For this study, I considered three alternative measurements. First, one could hire human coders asking them to evaluate on a Likert scale (Likert 1932) how controversial some content is, as used, e.g., in Chen

[12] I thank Benjamin Schiller, Simon Moselewski, Sebastian Kliehm and Patrick Felka for their excellent support in data collection.

and Berger (2013). This measurement is however less applicable for large data sets. As an alternative to the hand-coded measurement, I consider two proxies.

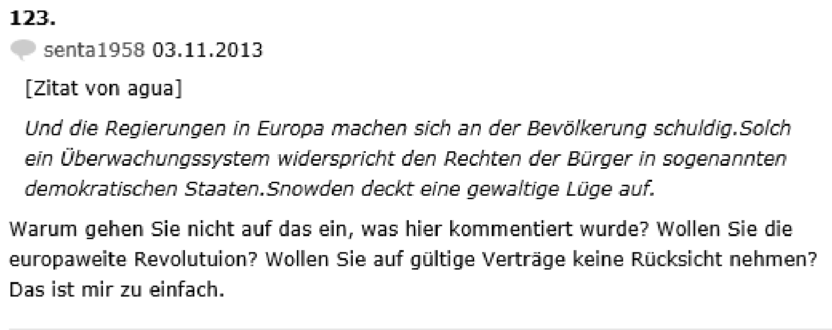
123.
senta1958 03.11.2013
[Zitat von agua]
Und die Regierungen in Europa machen sich an der Bevölkerung schuldig.Solch ein Überwachungssystem widerspricht den Rechten der Bürger in sogenannten demokratischen Staaten.Snowden deckt eine gewaltige Lüge auf.
Warum gehen Sie nicht auf das ein, was hier kommentiert wurde? Wollen Sie die europaweite Revolutuion? Wollen Sie auf gültige Verträge keine Rücksicht nehmen? Das ist mir zu einfach.

Figure 10. Structure of comments on *Spiegel Online*

First measurement constitutes the number of search results to the topic of the article plus the word "controversy" in German. For that purpose, I collect the keywords of the articles from the *Spiegel Online* website, e.g., "Edward Snowden", "Cats", or "Weather" as a description of the article's topic. Then I implemented a proprietary application which uses the Bing Application Programming Interface (API) to sum up the number of search results when entering each keyword in a "Keyword + controversial" pair. This approach proofed to lack reliability, as for some keywords, the results were fuzzy and implausible. As pointed out by Chen and Berger (2013), "controversy is on the eye of the beholder" and could be highly subjective for the conversation partner depending on the cultural and personal background and experiences. This could be the reason why this measure for controversy did not perform too well.

Finally, I decide to use a measure similar to the one presented by Gómez et al. (2008). They propose to measure how controversial a conversation is by looking at the number of threads in the discussions on Slashdot. Then, this idea was implemented using web crawlers to collect the comments for each article on the *Spiegel Online*'s website and count how often users comment on someone other's post. Figure 10 shows exemplarily the structure of comments on *Spiegel Online*. The user "senta1958" is quoting or replying to the post by "agua". I assume that the higher the number of replies to other user's posts, the more controversial is the conversation topic. Usually, the users are quoting the previous posts if they disagree about the opinions or do not share the attitudes of other users.

4.3.3 Additional controls

As discussed in Section 2.6, there are other factors that influence social sharing. Therefore, I control for the content's positivity, emotionality and emotional dimensions of anger, sadness and anxiety. I calculate these variables using an automated tool for sentiment analysis LIWC (Pennebaker et al. 2007). Positivity measures the difference between the shares of positive and negative words. Emotionality pertains to the share of positive and negative words. Web crawlers captured the sections where an article was published, e.g., politics, business, science, etc. Finally, I control for the number of words and the number of images as they can make the content more appealing, a factor that could ultimately drive social sharing (Dellarocas et al. 2015; Strufe 2010).

To examine whether some content is more commented or rather "liked" or both, I employ a variable that measures the ratio of the number of comments to the number of Likes. Before calculating this variable, I normalize the number of comments and number of Likes dividing each value by the respective highest observed values with the purpose to ensure the comparability of these two measures. The variable for the ratio of comments and Likes amounts to one, if the content gains a comparable amount of social sharing occurrences on the discussion board and on Facebook. It takes on values greater than one, if there are significantly higher social sharing activities on the discussion board.

Further, I standardize the variables which measure positivity and emotionality of the content as well as the degree at which it evokes emotions anger, anxiety and sadness. Table 22 provides a brief description of the variables and the data sources.

Variables	Source	Description
#Likes	Captured by web crawler	Number of Likes an article received in two weeks after publishing
#Comments	Captured by web crawler	Number of comments an article received in two weeks after publishing
Ratio #Comments to #Likes	Calculated from the data set	Ratio of comments to Likes
Controversy	Captured by web crawler	Approximated by the share of threads in the number of comments
Positivity	Calculation based on the results of sentiment analysis (LIWC)	Difference between the share of positive and negative words in the article
Emotionality	Calculation based on the results of sentiment analysis (LIWC)	The share of positive and negative words in the article
Anger	LIWC	The share of words in the article related to anger
Anxiety	LIWC	The share of words in the article related to anxiety
Sadness	LIWC	The share of words in the article related to sadness
Section Dummies	Captured by web crawler	e.g. 1= article appeared in science section; 0 = otherwise
Article length	LIWC	Number of words in the article
# images	Captured by web crawler	Number of pictures in the article
Day t	Calculation from the data set	Calendar date

Table 22. Model variables

4.4 Results

4.4.1 Descriptive statistics

Table 23 provides summary statistics of the variables used in this study. Most articles in the sample are related to politics (24%) followed by articles related to societal events and news (16%) and business (11%). As depicted in Figure 11, the number of Likes and the number of comments are right-skewed following a Zipf's law distribution – very few articles receive a high attention in social media, whereas many articles receive very few Likes or zero comments.

Variable	Percentage of sample	M	SD	Min	Max
# Likes		681.70	1621.45	3	19014
# Comments		79.30	114.77	0	881
Ratio # Comments to # Likes		11.72	22.01	0	230.93
Controversy		.28	.22	0	.87
Positivity[a]		.52	1.54	-6.9	6.63
Emotionality[a]		3.63	1.32	0	10
Anxiety[a]		.18	.27	0	4.55
Anger[a]		.38	.50	0	3.45
Sadness[a]		.28	.33	0	2.93
D_Science	6%				
D_Sports	10.09%				
D_Cars	5.13%				
D_Technology	7.13%				
D_Business	11.30%				
D_Health	2.96%				
D_Culture	7.22%				
D_Society	16.26%				
D_Politics	23.74%				
D_Travel	3.30%				
D_Education	6.87%				
# Words		590.51	322.95	4	2929
# Images		.64	1.14	0	20

[a] before standardization

Table 23. Summary statistics

Furthermore, Table 24 and Table 25 present the top ten most commented and most "liked" articles. In line with the hypotheses, these lists consist of completely distinct articles. Whereas articles most shared on Facebook are related to less controversial topics like kids (bat kid and cuddling twins), food and health, weather and societal news, most commented articles are related to politics and critical societal issues and concerns. Metaphorically speaking, articles shared on Facebook are appropriate for discussing at a dinner table or in small talks.

Two of the top commented articles are related to the US wiretapping scandal and to the whistleblower Edward Snowden, a topic that had wide news coverage in the year 2013 in Germany. As reported by the Pew Research Center (Hampton et al. 2014), Germans are apparently also less willing to discuss such politically explosive issues on Facebook. Also the scatter plot in Figure 12 lacks a positive correlation and thus attests that the most commented articles are not the most ones shared on Facebook.

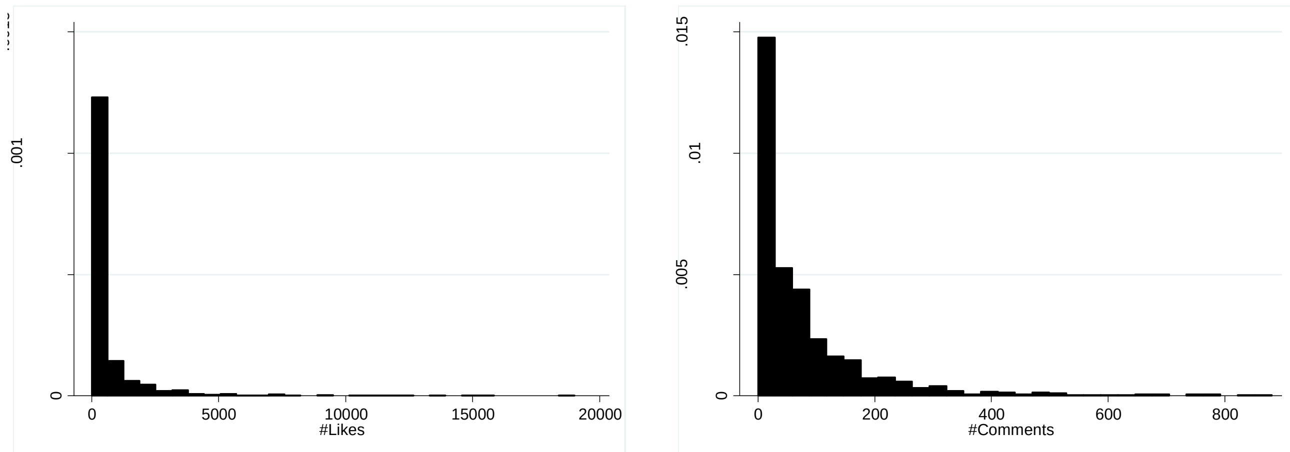

Figure 11. Distribution of # Likes and # Comments

# Comments	German title and English translation
881	*Schlaue Stromzähler: Regierung bereitet neue Zwangsumlage für Stromkunden vor* Smart meter: Government prepares new cost allocation for energy customers
850	*US-Abhörskandal: Bundesregierung lehnt Asyl für Snowden ab* US wiretapping scandal: German Government declines asylum for Snowden
779	*Asyl für Snowden: "Welcome Edward!"* Asylum for Snowden: „Welcome Edward!“
775	*Im Zweifel links: The ZDF und der kritische Journalismus* In doubt left-wing: the ZDF and the critical journalism
744	*Hartz IV in der Familie: Jobcenter setzt Schüler unter Druck* Hartz IV in families: Job center puts pressure on pupils
739	*Im Zweifel links: Deutschland fällt in den Tiefschlaf* In doubt left-wing: Germany falls in hibernation
680	*Atomenergie: Klimaforscher fetzt sich mit Umweltverbänden* Nuclear power: Climate scientist quarrels with environmental organizations
677	*Autobahn-Maut: Ministerium prüft 100-Euro-Vignette* Highway toll: Ministry examines the 100 Euro road tax disc
672	*Fall Redtube: Kanzlei plant weitere Abmahnungen für Porno-Streaming* Case Redtube: Chancellery plans further warnings for porn streaming platforms
648	*Umstrittenes Koalitionsprojekt: Die Mietpreisbremse hilft nur den Reichen* Controversial project of the coalition: Limitation of rental prices helps only the riches

Table 24. Top 10 commented *Spiegel Online* articles

# Likes	German title and English translation
19,014	*Neues Kabinett: Von der Leyen wird Verteidigungsministerin* New ministry: Von der Leyen will be the defense secretary
15,659	*Rückrufaktion in Supermärkten: Molkerei warnt vor gefährlichen Bakterien in Reibekäse* Recall campaign in super markets: Dairy warns of dangerous germs in grated cheese
14,662	*"Fast and Furious"-Star: Schauspieler Paul Walker stirbt bei Autounfall* „Fast and Furious" Star: Actor Paul Walker dies after car accident
13,693	*Kuschelnde Zwillinge: Unzertrennlich auch nach der Geburt* Cuddling twins: Inseparable after the birth
12,585	*Legendäre Komikergruppe: Monty Python planen Wiedervereinigung* Legendary comedian band: Monty Python plan a reunion
11,648	*Ungerechtes Bildungssystem: Ein Junge will nach oben* Unfair educational system: A boy wants up the social ladder
11,557	*Firmen-Webseite: McDonald's rät Mitarbeitern von Fast Food ab* Firm website: McDonalds's advises employees against Fast Food
11,236	*Fünfjähriger als Batkid: Superheld für einen Tag* Five years old bat kid: Superhero for one day
10,922	*Weihnachten im Kölner Dom: Femen-Aktivistin springt vor Kardinal Meisner nackt auf Altar* Christmas in the cathedral of Cologne: A naked Femen activist jumps on the altar in front of the cardinal Meisner
10,768	*Sturmflut an der Nordsee: Orkantief bedroht weite Teile Deutschlands* Storm flood at the North Sea: Low-pressure system threatens large parts of Germany

Table 25. Top 10 *Spiegel Online* articles shared on Facebook

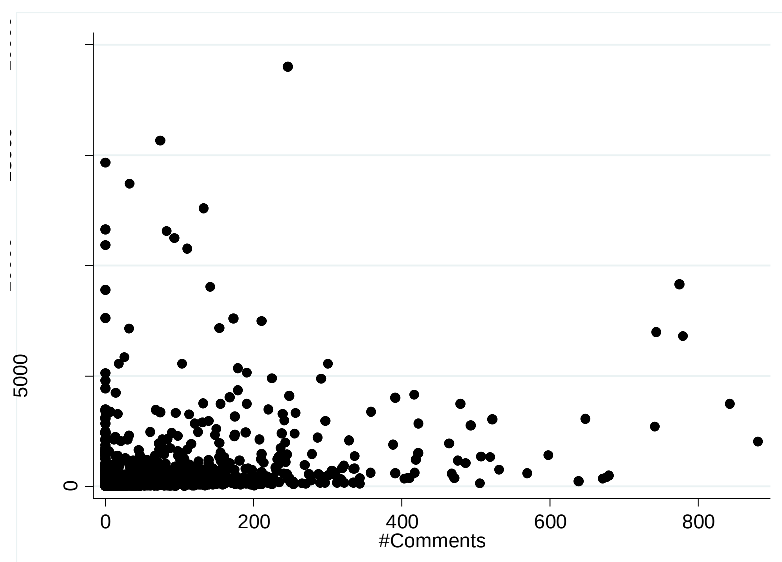

Figure 12. Scatter plot of #Comments in the discussion board and #Likes on Facebook

4.4.2 Results of regression analysis

I estimate the data using ordinary least square regression with fixed effects for the day of publishing. I use robust standard errors to account for heteroscedasticity.

Variable	(1) Ratio #Comments to #Likes	(2) Ratio #Comments to #Likes	(3) Ratio #Comments to #Likes
Controversy	-6.436	-0.642	37.62***
	(-0.76)	(-0.07)	(12.89)
Controversy^2	67.62***	63.91***	
	(4.00)	(3.58)	
Positivity	-0.356		
	(-0.40)		
Emotionality	1.080		
	(0.93)		
Anxiety	-0.441		
	(-1.08)		
Anger	-0.866		
	(-1.01)		
Sadness	0.436		
	(0.73)		
D_Science	-4.952*		
	(-2.58)		
D_Sports	20.68***		
	(6.50)		
D_Cars	18.60***		
	(3.77)		
D_Technology	7.697**		
	(3.53)		
D_Business	5.768**		
	(2.92)		
D_Health	-1.959		
	(-1.25)		
D_Culture	0.0167		
	(0.01)		
D_Society	2.915		
	(1.50)		
D_Politics	5.400***		
	(3.79)		
D_Education	-2.617		
	(-1.80)		
# Words	0.003		
	(1.82)		
# Images	-0.577		
	(-1.06)		
Constant	-2.317	3.636***	1.040
	(-1.19)	(6.42)	(1.26)
N	1150	1150	1150
adj. R^2	0.251	0.157	0.140
Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$			

Table 26. Estimation results of fixed effects model

Table 26 presents the estimation results. Articles related to travelling build the reference category in the estimation model. Model 1 is the full model, models 2 and 3 show the estimation results without additional controls to attest the robustness of the findings. The results of F-tests (all p < .001) indicate that at least one of the variables can explain the variation in the dependent variable.

The adjusted R^2s are quite good for all models indicating that the models capture large parts of the variance that explains the ratio of number comments and number of Likes.

With respect to the main variable of interest I find an inverted U-shaped relationship between the controversy and the likelihood of being discussed on discussion boards ($p < .001$). The findings from regression analysis indicate that articles that exhibit high amount of controversy are rather discussed on discussion boards than shared on Facebook.

The additional content controls (positivity, emotionality, anger, sadness are anxiety) are not significant. The results of this study show that positively and highly emotionally written content that evokes anger, anxiety or sadness has no particular effect on the increased amount on conversations in discussion boards. With respect to the articles' sections, we see that articles related to sports, cars, technologies, business and politics are relatively more often discussed in discussion boards than shared on Facebook. In contrast, articles related to science seem on average gain more social sharing activities on Facebook than.

4.5 Summary and Discussion

I examine a sample of articles from the German online news magazine *Spiegel Online* and find that controversial content is shared less often on Facebook while it is actively discussed on discussion boards. These results are important for a number of decisions.

First, most content providers start to pay less attention to discussion boards as interaction platforms with their readers or even abolish them and encourage their readers to switch to Twitter, Facebook and Google+ like the technology news provider *Re/code* or the German online newspaper *Süddeutsche Zeitung*. *Süddeutsche Zeitung* restricted, for example, the commenting function to three articles per day[13]. The readers were then very displeased about this decision (Breithut 2014).

This research also contributes to the debate about anonymous communication on the Internet (Davenport 2002). Many content providers require registration with real names instead of pseudonyms these days and many news magazines are rethinking the commenting functions on their websites (Pérez-Pena 2010). The results show that under the condition of anonymity, the users are more willing to discuss controversial topics and openly reveal their opinion. From a global societal perspective, it is important that the critical topics are not getting lost in the spiral of silence. As argued by the advocates of identity disclosure, people tend to say nasty and ugly things or behave aggressively when they feel unobserved or their behavior is not accountable to their personalities. But I believe it is necessary for the well-being of democracy and the formation of a free public opinion that people can voice their opinions also under the condition of anonymity. Social media teams should, for example, sort out user comments that violate the netiquette. The strategy of some content providers to require registrations with real names – as required by the most social media – is not appropriate and hinders an open discourse. Under the non-anonymous sharing mechanisms, people therefore tend to share rather conformist content.

[13] http://www.sueddeutsche.de/kolumne/ihre-sz-lassen-sie-uns-diskutieren-1.2095271

This study is not without limitations. First, the results are based on observational data from only one magazine and the generalizability of the findings should be tested for other content providers and other social media. Second, there might be a selection bias. The users of discussion boards could substantially differ from users that participate in social media and thus the differences with respect to online conversations might be due to user heterogeneity. Third, the results of the study are not necessarily causal. To address these shortcomings, future research might analyze data from different content providers, test the generalizability of the findings, and conduct laboratory experiments to test the causality of the effects.

5 PAYING INCENTIVES FOR SOCIAL SHARING[14]

5.1 Introduction

This study analyzes how the payment of incentives affects social sharing, particularly the willingness to make referrals and writing of consumer reviews. As discussed in Section 2.7.9, some online and offline retailers and service providers pay incentives for the consumers to generate more social sharing occurrences. While most of the research on social sharing incentivization focuses on the impact of different incentives on making referrals (Jin and Huang 2014; Wirtz et al. 2013), this study addresses how the incentive may generally affect (1) the likelihood to refer, (2) overall content evaluation and (3) writing of a consumer review as a particular form of social sharing messages.

Conventional wisdom would suggest that paying incentives motivates the customers to be more likely to refer the content and to put more effort into the writing of reviews. The theory on money-market relationship supports this idea (Fiske 1992; Heyman and Ariely 2004), as incentives might dissolve social relationship norms. On the other hand, as shown in several studies from the field of behavioral economics (for summary, see e.g. Kamenica (2012)), paying incentives could backfire on the companies' intentions. The customers might think that a company is trying to bribe him or her into generating a positive word of mouth so that the customers might be less willing to refer the content or to write a consumer review or might even write less positive reviews. Moreover, the customers might indeed feel that the company rewards them for their service and consequently write positively biased reviews, which is not so bad for the company at first glance. However, in the long run, other customers might become aware of such paid reviews (as they are written in a more professional manner) and will gradually lose confidence in those reviews. This would threaten or even ruin the entire concept of word of mouth marketing.

The following three field experiments address therefore this question. In all three studies, the customers were asked to evaluate the services of a car dealership and of a university cafeteria. Hereby, the subjects in the treatment group received a monetary incentive for their next purchase; the subjects in a control group were not rewarded for their service. As discussed in Section 2.2, social sharing is important in any purchase decision, but it is especially crucial in the service context, because services represent information goods for which their quality judgement is not possible before consumption (Nelson 1970).

The Section 5 is structured as follows. First, I present the conceptual model and derive hypotheses. Afterwards, I describe the experimental design and report the results from the three field studies. Finally, I discuss the overall findings.

[14] Parts of this study are presented as Heimbach and Kim (2016) "The Effects of Monetary Incentives on Word of Mouth Generation" on the 45th Conference of the European Marketing Academy (EMAC), in Oslo, Norway, 24-27 May 2016.

5.2 Hypotheses Development

As discussed in Section 2.2, consumers' decision to engage in social sharing is a „function of the cost/ benefit analysis by the potential influencer" (Gatignon and Robertson 1986). Previous research identifies motives, such as showing professional expertise, helping others, pursuing self-enhancement motives (Hennig-Thurau et al. 2004; Sundaram et al. 1998) and also simply venting negative emotions related to the experience with the content (Berger 2014). The costs related to the decision to engage in social sharing are time, effort spent on and social costs of communication (Gatignon and Robertson 1986). Therefore, people who engage in social sharing constitute a population subsample for which the benefits outweigh the costs. Consequently, if companies are paying incentives in exchange for making referrals and writing reviews, they change the cost-benefit ratio of consumers and thus they will also attract additional consumers who would not have engaged in social sharing otherwise. Thus:

Hypothesis 1: *If the customers receive a monetary incentive, they are more willing to engage in social sharing.*

The effects of paying incentives on the overall evaluation and on the message valence are unclear. It mainly depends on which types of customers will be attracted to engage in social sharing, if any. The previous research on social sharing messages reports that only consumers that are extremely satisfied or dissatisfied with the content generate such messages (Anderson 1998; Bowman and Narayandas 2001; Mazzarol et al. 2007). People who exhibit moderate levels of satisfaction are rather not willing to engage in social sharing. If companies are paying incentives, they also might attract customers with moderate levels of satisfaction. This would decrease consequently the average evaluation and valence, if the groups of customers who engage in social sharing are extremely satisfied and this will increase the average evaluation and valence if the customers are generally rather unsatisfied. If the customers who engage in social sharing are equally dispersed, the overall evaluation would stay unchanged. Table 27 shows these hypothetical scenarios. Consider three customers who would share their content evaluation under an unpaid condition (1 = very bad, 5 = very good). Assuming that a forth customer with a moderate evaluation would be willing to give an evaluation; we can observe different outcomes with respect to the new overall evaluation. These scenarios assume, however, that the payment of incentives does not influence customers who would share their evaluations without receiving monetary or non-monetary rewards. However, the very offering of a reward could alienate extremely satisfied customers because they might feel themselves offended and bribed. Also, it could be possible that unsatisfied customers under the paid-condition might feel being compensated for the poor content quality and evaluate less critical. Therefore, I formulate three competing hypotheses:

Hypothesis 2a: *If the customers receive a monetary incentive, the likelihood to refer and the average evaluation will decrease.*

Hypothesis 2b: *If the customers receive a monetary incentive, the likelihood to refer and the average evaluation will increase.*

Hypothesis 2c: *If the customers receive a monetary incentive, the likelihood to refer and the average evaluation will remain unchanged.*

Customers' evaluation under the unpaid condition	**Mean evaluation**	**+ customer with moderate level of evaluation**	**Evaluation change**
(1,1,1)	(1+1+1)/3 = 1	+3	(1+1+1+3)/4 = 1.5
(5,5,5)	(5+5+5)/3 = 5	+3	(5+5+5+3)/4 = 4.5
(1,3,5)	(1+3+5)/3 = 3	+3	(1+3+5+3)/4 = 3

Table 27. Calculation example

While investigating how the incentives affect human behavior, one should consider that human social interactions take place under two modes: money-market and social-market relationships (Fiske 1992; Heyman and Ariely 2004). Money market is associated with business transactions where money is usually involved in immediate exchange of content of similar values. In contrast, social market refers to friendship relationships where the transactions do not involve money. Heyman and Ariely (2004) show in three laboratory experiments that individual willingness to help increases with the increasing payment level (money-market). Thus, customers may put more effort into the writing because they are rewarded for their service, leading to:

Hypothesis 3: *If the customers receive a monetary incentive, they write longer messages.*

Hypothesis 4: *If the customers receive a monetary incentive, they write more readable messages.*

Hypothesis 5: *If the customers receive a monetary incentive, they write two-sided messages.*

While putting more effort into the writing on one hand, the professionality within the money-market may push back all emotionality which is usually perceptible in a message, i.e. incentives might prime customers to market exchange norms and see product evaluations as a kind of business transactions. Thus:

Hypothesis 6: *If the customers receive a monetary incentive, they write less emotionally.*

Hypothesis 7: *If the customers receive a monetary incentive, they write more factual messages.*

These hypotheses are then tested in the following three field experiments.

5.3 Study 1

Study 1 was conducted to get a general idea how the payment of incentives influences the customers' service evaluation and referral likelihood.

5.3.1 Method, procedure, and participants

The first study uses between-subjects design in which the incentive offering is varied (treatment: reward vs. control: no reward). The experiment took place during a tire change campaign of one local car dealership at two Saturdays and three work days in November from 10^{th} to 17^{th} 2012 in Darmstadt (Germany). The campaign lasted for two weeks. For that purpose the customers could register in advance and choose their preferred time slots. 175 customers registered for the service. The tire change service was scheduled to take 30 minutes. While waiting for the completion of the tire change service, the car dealership offered free coffee and the student research assistant[15] contacted then the customers.

For the treatment group the car dealership offered 5€ coupons for its products and services. As customers could register in advance for the service and book their preferred time slots, I expect that the results are not biased e.g., due to longer waiting times at some days. Further, the customers in the treatment and control conditions were equally distributed over the Saturdays and work days. Therefore, I assume no selection bias due to the choice of the experiment timing, such as a particular type of customers would prefer to come at Saturdays.

A paper-based questionnaire was developed together with the car dealership owner. The customers were asked to give an overall evaluation for the car dealership service, their intention to refer the service and to share positive word of mouth. Further, they were asked to evaluate specific service dimensions like availability, car repair services and the tire change campaign. As shown by previous research, specific personal characteristics like altruism (Hennig-Thurau et al. 2004; Ho and Dempsey 2010) or price consciousness (Kim et al. 2009) might influence the social sharing behavior; therefore, the customers were asked for these characteristics. Finally, the data on customers' gender, age, education, and income levels was collected. Table 28 presents the structure of the questionnaire.

The customers were not informed about the research question and were only told to participate in the survey of the car dealership to improve the service. 27 customers denied participation, resulting in 85% response rate. The customers were randomly distributed to two conditions with respect to gender ($\chi^2(1) = 0.01$, $p < .91$), and education levels ($\chi^2(4) = 1.30$, $p < .73$). However, the random assignment to the experimental conditions failed with respect to income ($\chi^2(9) = 25.81$, $p < .01$) and age ($\chi^2(9) = 17.25$, $p < .05$). Also, the customers in both conditions were similar with respect to price consciousness ($\alpha = 0.63$, control: $M = 2.08$ vs. treatment: $M = 1.95$, $p < .18$) and altruism ($\alpha = 0.87$, control: $M = 1.66$ vs. treatment: $M = 1.77$, $p < .12$).

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[15] I thank Sven Pongratz for his valuable help by the data collection. Additionally, I gratefully acknowledge car dealership owner Mr. Moya for enabling the conduction of this field experiment.

Construct	Items/ Scale
How is your overall satisfaction with our services?	1 = very good; 6 = very bad
How is your overall evaluation of the car dealership?	1 = very good; 6 = very bad
How likely would you recommend our service to others?	1 = very likely; 6 = not at all
How likely would you share positive word of mouth about our service?	1 = very likely; 6 = not at all
Reputation (adapted from Selnes (1993))	• Our reputation is better than from other car dealerships. • You tell that you are our customer. 1 = very likely; 6 = not at all
Evaluation of the tire change campaign	
The time schedule was appropriate.	1 = very good; 6 = not at all
The service was professional.	1 = very good; 6 = not at all
The service employees were kind.	1 = very good; 6 = not at all
Previous experience with the car repair services	
The employees reserved sufficient amount of time for my concerns.	1 = very good; 6 = not at all
I did know in advance which services should be done at my car.	1 = very good; 6 = not at all
The bills were comprehensible.	1 = very good; 6 = not at all
Time schedules and appointments were kept.	1 = very good; 6 = not at all
Availability	
Availability of the employees in the store	1 = very good; 6 = not at all
Availability by free answer card	1 = very good; 6 = not at all
Availability by email	1 = very good; 6 = not at all
Availability by fax	1 = very good; 6 = not at all
Availability by phone	1 = very good; 6 = not at all
Price consciousness (Donthu and Gilliland 1996; Kim et al. 2009)	• Before buying a product, I compare the prices of different sellers. • I usually purchase items on sales only. • By similar products, I usually purchase the cheapest one. 1 = very likely; 6 = not at all
Altruism (Costa and McCrae 1992)	• I love to help others. • I am concerned about others. • I make people feel welcome. • I anticipate the needs of others. 1 = very likely; 6 = not at all
Gender	1 = male; 0 = female
Age	11 groups
Education level	4 groups
Income level	11 groups

Table 28. Questionnaire used in Study 1

5.3.2 Results

Under the paid treatment condition, 72 customers filled out the questionnaire, whereas 76 customers participated in the non-paid control condition. Interestingly, 16 people in the treatment group (about 18%) and 11 people in the control group (about 12%) refused to participate in the study. This contradicts hypothesis 1 that under the paid condition people would be more willing to engage in social sharing.

With respect to the overall evaluation of the car dealership, there is a significant difference between the two groups. The customers under the paid condition evaluated the car dealership service significantly worse (M = 1.65) compared to the non-paid condition (M = 1.44, $p < .05$). Similarly, they were less willing to refer the services to their friends (treatment: M = 1.70 vs. control: M = 1.47, $p < .05$) and generally to share positive word of mouth (treatment: M = 1.70 vs. control: M = 1.39, $p < .01$). Further, the customers in the paid condition evaluated the reputation significantly worse (M = 1.86) compared to the non-paid condition (M = 1.38, $p < .01$). Finally, the customers of both groups were equally satisfied with the services (treatment: M = 1.50 vs. control: M = 1.61, $p < .13$) and showed no significant differences with regard to their evaluation of the tire change campaign, their previous experience and the availability.

Overall, the findings of the first study suggest that the payment of incentives for social sharing activities is detrimental on the content evaluation, reputation and the willingness to refer it to friends and to share positive word of mouth. As the random assignment did not work with respect to income and age, these findings could be attributed to these differences between the groups. Further, this study did not include manipulation checks. Therefore, no hints on the drivers of worse evaluation and decreased willingness to refer to friends and to share positive word of mouth could ne given. The second study replicates therefore this study and includes more variables to capture all possible aspects of social sharing behavior.

5.4 Study 2

5.4.1 Method, procedure, and participants

The second study again applies the between-subjects design (treatment: reward vs. control: no reward). The experiment took place from September 7th to 19th 2015 (two weeks), daily at peak times between 7:30 a.m - 9.30 a.m. and 4:00 p.m. - 6:00 p.m. in Darmstadt (Germany) in the same local car dealership as in the first study.

For the treatment group the car dealership offered again 5€ coupons for its products and services. During the first week the customers did not get a coupon (control), but in the second week (treatment). The paper-based questionnaire was again developed together with the car dealership. A student research assistant[16] asked to fill out the questionnaires. The customers were asked to give an overall evaluation for the car dealership service, their intention to refer the service and to share positive word of mouth. Further, we asked for customers' gender, age, education, and income levels. In contrast to Study 1, price consciousness was excluded and extraversion was included. Additionally, several manipulation checks were included. Table 28 presents the final questionnaire.

The customers were not informed about the research question and were only told to participate in the survey of the car dealership to improve the service. The student research assistant contacted 96 customers; 26 customers denied participating in the experiment, resulting in 72.92% response rate. The customers were randomly distributed to two conditions with respect to gender ($\chi^2(1) = 0.94$, $p < .33$), education levels ($\chi^2(3) = 4.82$, $p < .19$), to income levels ($\chi^2(5) = 3.86$, $p < .57$) and age ($\chi^2(9) = 13.49$, $p < .14$). Also, the customers in both conditions were similar with respect to extraversion (control: 3.57 vs. treatment: 3.17, $p < .07$) and altruism (control: 1.99 vs. treatment: 2.20, $p < .18$).

5.4.2 Results

Under the paid treatment condition, 33 customers filled out the questionnaire, whereas 37 customers participated in the non-paid control condition. Similar to the first study, more people in the treatment group (14, about 30%) refused to participate in the study compared to the control group (12, about 25%). This contradicts again the hypothesis that under the paid condition people would be more willing to engage in social sharing. From the resulting 70 responses three were discarded due to sparsely filled questions (one from the control group, two in the treatment group).

With respect to the overall evaluation of the car dealership, there is no significant difference between the two groups ($M = 1.26$, $p < .50$). With respect to the overall satisfaction, the paid group give worse evaluation ($M = 1.54$) which is weakly significant, compared to the non-paid

[16] I thank again Mr. Moya for giving another opportunity to conduct this field experiment and Christian Tran for his great assistance by the data collection.

condition ($M = 1.35$, $p < .10$). Also, they were less willing to refer the services to their friends (treatment: $M = 1.70$ vs. control: $M = 1.47$, $p < .05$).

Construct	**Items/ Scale**
How is your overall satisfaction with our services?	1 = very good; 6 = very bad
How is your overall evaluation of the car dealership?	1 = very good; 6 = very bad
How likely would you recommend our service to others?	1 = very likely; 7 = not at all
Service evaluation	
I always get service without delays.	1 = very good; 7 = not at all
I have a feeling that the car dealership meets my interests at best.	1 = very good; 7 = not at all
By problems, the causes are found and managed quickly.	1 = very good; 7 = not at all
I did know in advance which services should be done at my car.	1 = very good; 7 = not at all
The car dealership is always available.	1 = very good; 7 = not at all
I can always rely on the car dealership.	1 = very good; 7 = not at all
Time schedules and appointments were kept.	1 = very good; 7 = not at all
Employees evaluation	
The service was professional.	1 = very likely; 7 = not at all
The service employees were kind.	1 = very likely; 7 = not at all
The employees are always willing to help.	1 = very likely; 7 = not at all
I trust the employees of the car dealership	1 = very likely; 7 = not at all
I get personal, individual attention from the employees	1 = very likely; 7 = not at all
Relationship with the car dealership	
If I have a problem, I come to the car dealership.	1 = very good; 7 = not at all
If the service quality remains unchanged, I would not change the car dealership.	1 = very good; 7 = not at all
By buying a car, the car dealership is my first choice.	1 = very good; 7 = not at all
I am very satisfied with the car dealership.	1 = very good; 7 = not at all
I use the website to inform about the products and services	1 = yes; 0 = no
I use Facebook fan page to get news	1 = yes; 0 = no
I miss a communication medium to get in contact with the car dealership	1 = yes; 0 = no, if yes, which one
I inform myself about the services/ sales on	1 = website; 2 = platforms; 3 = on Google; from newspaper announcements; 4 = word of mouth; 5 = from mailing lists
Extraversion (Costa and McCrae 1992)	• Feel comfortable around people. • Make friends easily. • Keep in the background • Don't like to draw attention to myself. 1 = very likely; 6 = not at all
Altruism (Costa and McCrae 1992)	• I love to help others. • I am concerned about others. • I make people feel welcome. • I anticipate the needs of others. 1 = very likely; 6 = not at all
Gender	1 = female; 2 = male
Age	10 groups
Education level	5 groups
Income level	7 groups, with “non-disclosure” option

Table 29. Questionnaire Study 2

Review dimensions	Measure
Volume	Number of posted reviews
Valence	The difference between the positive and negative words in the review text; calculated using LIWC (Pennebaker et al., 2007)
Length	Number of words Calculated using LIWC software Pennebaker et al. (2007)
Readability	Calculated using Flesh index; 100 = very easy, -20 very difficult (Study 2)
Sidedness	Manually coded: 1 = two-sided, 0 = one-sided
Emotionality	The share of all emotional words in the review text; calculated using LIWC (Pennebaker et al., 2007)
Review type	Manually coded, 1 = factual; 0 = experiential (Study 2) Manually coded; 7 = readable, 1 = not at all (Study 3)

Table 30. Measurement of consumer review dimensions in studies 2 and 3

With respect to the willingness to write a consumer review, 44% (14 out of 32) of customers under the paid condition wrote a review; in contrast, under the unpaid condition, only 23% (8 out of 35) ($p < .04$) wrote one. This provides support for the hypothesis that paying incentives facilitates the writing of consumer reviews. Further, I analyze the consumer review texts with respect to the dimensions valence, valence variance, emotionality, length, readability, sidedness and review type. Table 30 provides the overview how the different dimensions are measured. With respect to the valence and emotionality, paid customers wrote more positive (treatment: $M = 19.81$ vs. control: $M = 11.58$, $p < .10$) and more emotional reviews (treatment: $M = 20.82$ vs. control: $M = 13.57$, $p < .10$), albeit only weakly significant. With respect to the review length, readability, sidedness and review type, there were no significant differences.

Review dimension	Control	Treatment	P-value
Volume	44%	23%	.04
Valence	11.58	19.81	.10
Emotionality	13.57	20.82	.10
Length	19.25	22.29	.33
Readability	24.12	17.14	.33
Sidedness	.25	.22	.43
Review type	.63	.50	.30

Table 31. Review dimensions, group differences, Study 2

5.5 Study 3

The third study analyzes consumer review writing behavior in more detail. As Harrison-Walker (2001) notices that the effects of the customer satisfaction on the social sharing differs across industries, I analyze data from another service context, namely university cafeteria.

5.5.1 Method, procedure, and participants

The third study was conducted as a field experiment at a University cafeteria that usually serves up to 9,000 meals daily[17]. On two comparable days, 154 students filled out a questionnaire being asked about their experience with the cafeteria. Depending on the day, they either filled out the questionnaire for free (day 1: control condition) or they received a voucher of 1.50€, paid directly into their student card account, which serves as the general payment method for all cafeterias and vending machines (day 2: treatment condition). Both days were comparable regarding average sales, time of day and inquirer. The questionnaire consisted of four parts: first, respondents were asked to write a consumer review. Then, respondents could rate overall impression, prices and quality of meals, waiting time and friendliness of the cafeteria staff on a seven-point Likert scale with 1 = totally agree to 7 = totally disagree. The third part aimed to reveal the respondents' attitude towards monetary incentives given for consumer reviews. At last, the demographics were surveyed. The questionnaire was built similarly to that used in Study 2.

The customers were not informed about the research question and were only told to participate in the survey of the university cafeteria to improve the service. The cafeteria customers were randomly distributed to two conditions with respect to gender ($\chi^2(1) = .09$, $p < .76$), education levels ($\chi^2(4) = 4.27$, $p < .37$) and to income levels ($\chi^2(5) = 6.35$, $p < .27$) and their visiting frequency ($\chi^2(3) = 3.76$, $p < .29$). However, the paid group was slightly younger (control: M = 23.75 vs. treatment: M = 22.81, $p < .03$) than the unpaid group.

5.5.2 Results

Under the paid treatment condition, 94 students filled out the questionnaire, whereas 60 students participated in the non-paid control condition, which supports hypothesis 1. With respect to the overall evaluation of the cafeteria, there is no significant difference between the two groups (treatment: M = 3.55 vs. control: M = 3.54, $p < .53$). Also, they were equally willing to refer the services to their friends (treatment: M = 3.91 vs. control: M = 4.05, $p < .30$). Additionally, there were no differences in the evaluation of the cafeteria's service aspects like prices, meal quality and cafeteria staff.

With respect to manipulation checks, the customers in the paid group were happier about the payment of incentives (treatment: M = 2.22 vs. control: M = 2.89, $p < .01$). They also find it appropriate (treatment: M = 2.97 vs. control: M = 3.88, $p < .01$) and even desirable (treatment: M = 2.66 vs. control: M = 3.58, $p < .01$). Additionally, they denied that the payment of incentives

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[17] Many thanks to Ju-Young Kim and Lorenz Maierski from Karlsruhe Institute of Technology for the provision of data for the further analysis.

for writing of reviews made them skeptical (treatment: M = 5.22 vs. control: M = 4.08, $p < .01$), forced to give a better evaluation (treatment: M = 6.21 vs. control: M = 4.67, $p < .01$) and to refer the cafeteria to other people (treatment: M = 6.41 vs. control: M = 5.87, $p < .01$) as well as to feel being manipulated (treatment: M = 6.22 vs. control: M = 4.75, $p < .01$).

Further, I analyze the consumer review texts with respect to the dimensions valence, valence variance, emotionality, length, readability and review type. Table 30 provides the overview how the different dimensions are measured. With respect to the valence and emotionality, unpaid customers wrote more positive (treatment: M = 5.88 vs. control: M = 10.21, $p < .01$) and more emotional reviews (treatment: M = 12.08 vs. control: M = 15.89, $p < .05$). With respect to the review length and review type, there were significant differences between the paid and unpaid conditions. I find that respondents who received monetary incentives wrote significantly longer reviews (control: M = 21.03 vs. treatment: M = 33.81, $p < .01$) and used a more formal language (percentage of words captured by LIWC, control: M = 58.85 vs. treatment: M = 64.59, $p < .05$). Additionally, respondents in the paid condition wrote significantly more factual reviews than respondents in the control condition (treatment: M = 3.34 vs. control: M = 3.96, $p < .01$). Thus, the hypotheses 3 and 7 were supported.

Review dimension	**Control**	**Treatment**	**P-value**
Volume	60	94	n.a.
Valence	10.21	5.88	.01
Emotionality	15.89	12.08	.05
Length	21.03	33.81	.01
Review type	3.96	3.34	.01

Table 32. Review dimensions, group differences, Study 3

5.6 Summary and Discussion

Many online and offline stores set monetary incentives to solicit their customers to trigger social sharing in form of consumer reviews or personal referrals. However, practical and theoretical knowledge about the impact of such paid reviews and referrals on the sender's behavior is still scarce. This study examines how the provision of monetary incentives vs. no incentives affects social sharing. Analyzing the data from three field experiments, I find dissenting results. Table 33 summarizes the findings across the three field experiments.

With the respect to the willingness to engage in social sharing, the customers from card dealership were less willing under the paid condition. They were rather less likely to make referrals to their friends. However, the payment of incentives encourages writing more consumer reviews in Studies 2 and 3. Moreover, the reviewers put more effort into their writing: paid reviews are more likely to be longer and more factual. On the other hand, the results from the third experiment suggest that paid reviews were written less positive and less emotionally. Besides the effect that such reviews may be perceived as more professional, the receivers may sense the paid nature of the review, thus becoming more skeptical towards such emotionless and factual reviews (Schlosser 2011).

Studies	Study 1	Study 2	Study 3
Kind of incentive	5€ coupon	5€ coupon	1.5€ coupon
Study context	Car dealership	Car dealership	Student cafeteria
Study focus	Service evaluation and referral intention	Service evaluation, referral intention and writing a consumer review	Service evaluation, referral intention and writing a consumer review
More willing to engage in social sharing	No, the opposite is true	No, the opposite is true	Yes
Overall better evaluation	No, the opposite is true	No	No
Make more referrals	No, the opposite is true	No, the opposite is true	No
More consumer reviews	n.a.	Yes	Yes
More positive reviews	n.a.	Yes	No, the opposite is true
More emotional reviews	n.a.	Yes	No, the opposite is true
Length	n.a.	No	Yes
Readability	n.a.	No	n.a.
Sidedness	n.a.	No	n.a.
Review type	n.a.	No	Yes

Table 33. Summary of the findings from three experiments

This research project is not without limitations. First, all three studies were conducted in an offline context. As the most social sharing messages are written on online platforms, the kind of sharing mechanism might influence the kind of message, as discussed in the Section 2.7. In all three studies, the sharing mechanism could be seen as synchronous, such that the customers were forced to write the review immediately after the request. As the online setting might provide more time to think about the content (be as a product, service, or idea), the senders might put more effort into the crafting of social sharing messages. First evidence from the follow-up studies of this project indeed suggest that the senders in the online setting write even longer reviews compared to the offline setting. Further, this project reports contradicting results on the effects of incentive payments on the content evaluation, sharing likelihood and the wring style of the messages. Comparing the content types, the first two studies were conducted in the context of a car repair and dealership, the last study referred to the cafeteria. Car repair or dealership services differ from the cafeteria visits in terms of the visit frequencies. Moreover, the customers of car dealership might be more satisfied and loyal compared to students who often have to go for a meal to university cafeterias due to lack of alternatives. Last, these studies focus on the social sharing senders' perspective, research into the receivers' point of view is needed. The studies by Stephen et al. (2013) and Wirtz et al. (2013) build the first attempts to look how the receiver respond to the payment disclosure. This and other limitations offer promising future research directions.

6 THE IMPACT OF CONTENT SENTIMENT AND EMOTIONALITY ON CONTENT VIRALITY[18]

6.1 Introduction

As discussed in Section 2.5, the findings on the impact of sentiment and emotions on the diffusion of digital content are ambiguous. Communication research states that negative news earn more attention (Galtung and Ruge 1965). Hansen et al. (2011) find that negative news-“Tweets” are more likely to be re-tweeted but the popularity of non-news-“Tweets” relates to a positive sentiment of the content. De Angelis et al. (2012) find in a series of laboratory experiments that people tend to share positive word of mouth about their own experiences but tend to transmit negative word of mouth about the experiences of others. Berger and Milkman (2012) analyze the New York Times top list of the recommendations made per email and find that positively and emotionally written articles are more viral and confirm the causality of their findings by running laboratory experiments.

This study replicates the study by Berger and Milkman (2012) for German articles testing its generalizability in several ways. First, looking at a European sample allows an analysis of the cultural differences. Second, I investigate the content sharing on four different communication media (Facebook, Twitter, Google+ and e-mail) while Berger and Milkman (2012) investigated factors that make an article to go on the list with the most emailed articles of the New York Times. This allows therefore making more differentiated conclusions about the impact of sentiment and emotions on the virality of content.

6.2 Data

For this study I use data on *Spiegel Online* articles that appeared on the magazine’s webpage (www.spiegel.de) between March 1, 2012 and September 30, 2012 (27,375 articles). The data come from a large still ongoing project by Schiller et al. (2016). *Spiegel* counts as the leading German news magazine and it is one of Europe's largest publications of its kind. Using web crawlers Schiller et al. (2016) record the article’s title, link to the full text, the publishing date and the number of Tweets (Twitter), Likes (Facebook) and plus-ones (Google+) an article accumulated after two weeks after publishing. Similar to New York Times, Spiegel Online continually reports which articles made it to the top e-mailed ranking which consisted of five ranking positions 2012. I collect data about the most e-mailed lists in 2012 using the Internet Archive (https://archive.org/index.php) and match them with the other data set[19].

Following Berger and Milkman (2012), I exclude from the sample all video and images without texts (like “Picture of the day”). Additionally, I exclude blogs, live tickers, articles related to

[18] A substantially revised version of this study appears as Heimbach and Hinz (2016): "The Impact of Content Sentiment and Emotionality on Content Virality", International Journal of Research in Marketing, forthcoming.

[19] I thank Patrick Felka for his invaluable support by the data collection and Anne Schüßler and Sarah Wojcik for their help by data coding.

comics and jokes and articles that are no more available for further textual analyses, like press conferences and livestream news. The final data set contains thus 21,843 Spiegel online articles.

6.3 Article Coding

Following Berger and Milkman (2012), I use the German dictionary for automated sentiment analysis LIWC (Pennebaker et al. 2007) to quantify the positivity and emotionality of the articles in the sample. Positivity is determined as the difference between the shares of positive and negative words in article (Berger and Milkman 2012). Emotionality is quantified as the percentage of all positive and negative words in the article (Berger and Milkman 2012).

To also replicate the results for the specific emotional and content dimensions presented by Berger and Milkman (2012), a random sample of 311 articles (about 1.5%) is manually coded following the guidelines presented by Berger and Milkman (2012) (available on www.marketingpower.com/jmr_webappendix). Two coders were not informed about the research question and were asked to rate articles on a five-point Likert scale (Likert 1932) on the dimensions anger, awe, sadness, anxiety, interest, surprise, and practical utility. The inter-rater reliabilities were moderate (weighted Cohen's Kappas (Cohen 1968) were between 0.53 and 0.74, see Table 34) but acceptable. I averaged scores across coders and standardized them.

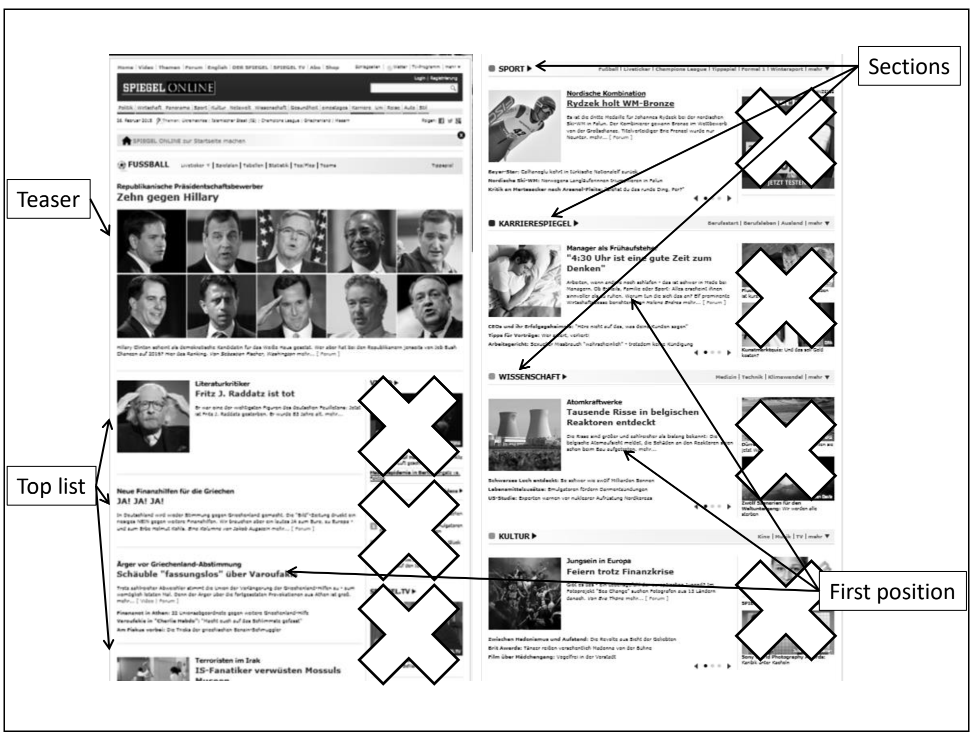

Figure 13. Landing page location categories

Further, I create controls for the different topic sections where an article has been published (see Figure 13). Articles are positioned most prominently in the teaser section, followed by the top featured articles section and the different category sections.

	Variable	M	SD	Min	Max	% of sample	weighted Cohen's kappa
# Likes		172.78	718.01	0	42679		
# Tweets		43.19	39.58	0	1132		
# Plus-ones		4.11	10.61	0	359		
Made it to most emailed list (0/1)						4.21	
Positivity[a]		.40	1.65	-11.9	12.77		
Emotionality[a]		3.59	1.40	0	14.12		
Anger[a]		2.29	1.18	1	5		0.74
Anxiety[a]		1.79	.94	1	5		0.66
Awe[a]		1.77	.86	1	5		0.55
Sadness[a]		1.88	1.02	1	5		0.62
Surprise[a]		2.48	.93	1	5		0.60
Practical utility[a]		1.70	.97	1	5		0.73
Interest[a]		3.11	.87	1	5		0.53
Coded						1.42	
Words x 10^{-3}		.66	.50	.04	6.68		
Release month	March					14.14	
	April					12.93	
	May					14.37	
	June					14.39	
	July					14.48	
	August					15.36	
	September					14.33	
Weekday	Sunday					9.60	
	Monday					15.12	
	Tuesday					16.10	
	Wednesday					16.57	
	Thursday					16.88	
	Friday					16.14	
	Saturday					9.59	
Released between 6am-6pm						70.15	
Released between 6pm-6am						29.85	
Sections	Science					5.90	
	Sports					15.74	
	Cars					2.20	
	Digital					5.91	
	Business					13.24	
	Health					1.48	
	Culture					8.51	
	Society					14.81	
	Politics					22.31	
	Travel					4.01	
	Education					4.76	
	History					1.11	
Complexity		35.64	11.75	-12	80		
Male first author						22.93	
Female first author						6.86	
Based on news agencies reports						70.21	
Released as top featured						21.84	
Released on first position						41.78	
Released as teaser						3.98	
Hours on landing page		23.41	93.32	0	3519.65		
Hours as top featured		3.44	59.26	0	2974.13		
Hours on first position		1.71	4.60	0	68.41		
Hours as teaser		.168	1.58	0	47.51		

[a] values before standardization, available only for manually coded articles

Table 34. Summary statistics

Within the teaser section, the top featured and the category section areas some articles could take the first position, appearing with a text teaser and often with accompanying images. When time elapses, articles are shown only as bullet points until they eventually disappear from the landing page. I also control for the time an article has spent on the landing page. 4,493 articles were not published on the landing page but only in subsections. The layout of Spiegel Online did not change during our observation period. I create controls for the month (6), weekday (7) and time of the day (6 a.m.-6 p.m. or 6 p.m.-6 a.m.) by using indicator variables for when the article appeared online. Further, I create an indicator variable which captures whether the first author is male or female or an article is based on news agencies reports. Finally, I control for the authors' writing complexity using the Flesch Reading Ease test (Flesch 1948) provided by an automated analysis tool, for the article length measured as word count and for the sections where the article appeared (see Table 34 for summary statistics and Table 35 for a correlation matrix).

6.4 Estimation Method

For the different subsamples I estimate different models. Due to the count nature of the data from online social media, I estimate a model using a Poisson regression with day specific fixed effects, clustering the standard errors by the publishing date. The estimation equation for sharing articles on Facebook, Twitter and Google+ looks as follows:

$$Prob(N\_Likes = N\_Likes_{it}|\boldsymbol{x}_{it}) = \frac{e^{-\lambda_{it}}\lambda_{it}^{N\_Likes_{it}}}{N\_Likes_{it}!} \text{ with } \lambda_{\text{it}} = e^{\boldsymbol{x}'_{it}\boldsymbol{\beta}+\varepsilon_t},$$

where N_Likes_{it} measures the number of recommendations for article i at day t and $\boldsymbol{x}_{it}$ is the vector describing article i on the different dimensions.

For the most emailed list I estimate a logistic regression – which is closest to the model presented by Berger and Milkman (2012) – with day specific fixed effects. The estimation equation looks as follows:

$$Prob(Mostemailed_{it} = 1|\boldsymbol{x}_{it}) = \frac{1}{1 + e^{-(\boldsymbol{x}'_{it}\boldsymbol{\beta}+\varepsilon)}}$$

For the small random subsample of hand-coded articles I do not estimate fixed effects models due to sparsely distributed data over the days. Instead, I estimate a logistic regression for the most emailed list and for three social media I estimate negative binomial regressions[20] including month and weekday dummies to control for the release date and using robust standard errors to account for heteroscedasticity.

6.5 Results

The models 1-4 (Table 36) present the results for the sample of manually coded articles, models 5-8 for the full sample. The Wald tests in all models show that at least one of the independent variables is not equal to zero (all p <.001 with the exception of Model 1).

[20] In contrast to the full sample where I use Poisson regression with fixed effects, I use negative binomial regression, because the latter captures better the distribution of the data in the small sample.

Overall, some findings across communication media are consistent but there are also some differences with respect to the study by Berger and Milkman (2012). I can confirm the positive relation of positivity and emotionality to content's virality, although this effect is not persistently significant for all communication media.

Models 5-8 show that the three dimensions anger, anxiety and surprise have a positive effect on sharing probability, a result which seems to be robust for social media as communication media in general. Anger evoking content goes viral in all three social media supporting findings by Berger and Milkman (2012) (*p* < .001). Similarly, surprise is positively related to content's virality (*p* < .001 for Facebook and Google+, *p* < .05 for Twitter) and anxiety inducing content is less likely to be shared by users with their peers via social media (*p* < .001).

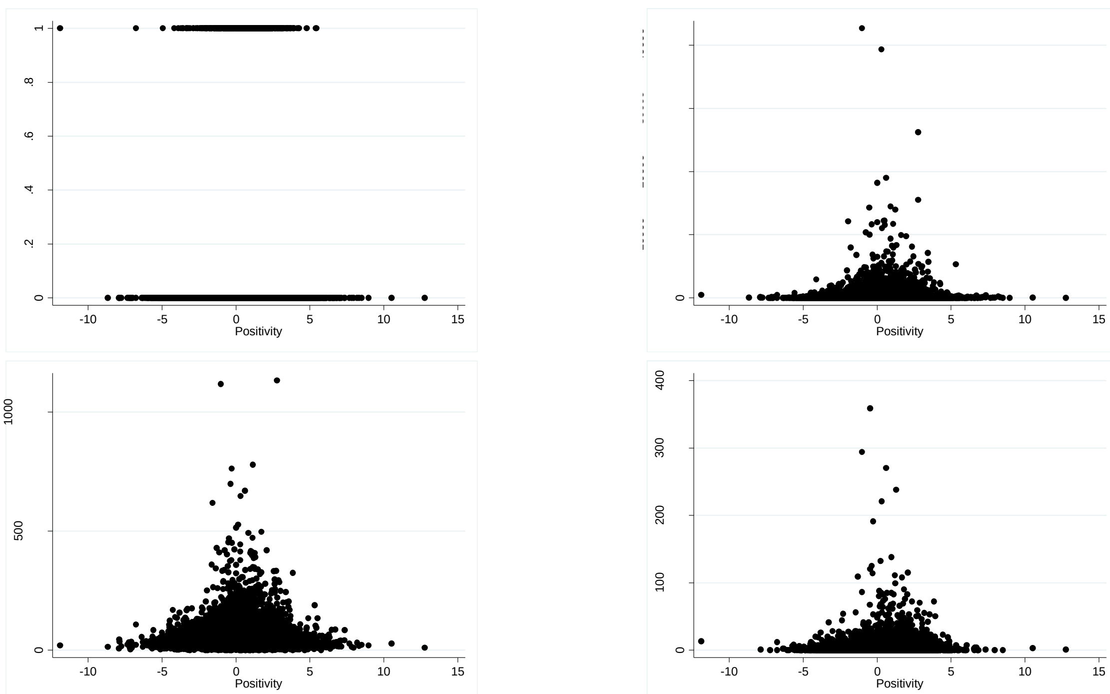

Figure 14. Scatter plots depicting the relation between positivity and the number of Likes, Tweets, One Ups and Most Emailed (0/1).

With respect to other content dimensions we observe subtle differences for the communication media: The effects for Facebook differ substantially from the results presented by Berger and Milkman (2012). While content that evokes awe and is of high practical utility goes viral on Twitter and Google+ (which is in line with the results presented by Berger and Milkman (2012)), the opposite is true for Facebook. The finding that useful content is less shared on Facebook supports the findings by Schulze et al. (2014), who reveal that utilitarian apps are less suited to be broadcasted on Facebook. Further, I find that sadness evoking content can go viral on Facebook which is also contradictory to the results presented by Berger and Milkman (2012) but in line with anecdotal evidences. For example, a very sad article about a drowned dog went viral, being with 62,229 Likes on Facebook one of the most shared articles in Germany in 2013. Likewise, interesting articles evoking awe have a lower probability to be shared on Facebook. These results could be partially explained by the high usage and user heterogeneity on Facebook.

On top of the findings, I find an inverted U-shape relationship between positivity and the number of recommendations in the respective communication media (as depicted in Figure 14). The models 9-12 in Table 36 show estimation results when a quadratic term for positivity is included[21]. With the exception of the most emailed list, the quadratic term of positivity is negative and highly significant for all three social media ($p < .001$). The effects of the other dimensions remain unchanged and for the number of Tweets the first term of positivity turns to be significant. The likelihood ratio test shows that including the quadratic term substantially increase the explanation power of the model ($p < .001$). This finding implies that content has an optimal level of positivity and that we cannot support the suggestion to craft content as positive as possible. Apparently, the users value objectively written articles which have a balanced amount of positive and negative words. Interestingly is this effect for the most emailed list model not significant. On the one hand, it supports the findings by Berger and Milkman (2012) and on the other hand it implies that there are differences between e-mail and social media as communication media or focusing on a binary dependent variable as in Berger and Milkman (2012) or for the most emailed list model leads to a loss of information. Future research might concentrate on these dissenting results.

6.6 General Discussion

In this replication study of Berger and Milkman (2012) for German articles in the context of four different communication media, I can largely confirm their results but the findings are also partially different. I find in the sample a positive relationship between emotionality and an inverted U-shaped effect between positivity and virality in social media. This can be caused by cultural differences but might also be a sign that sentiment in press articles are not highly valued by the audience as objectivity, neutrality and fact verification are more important than the frequent use of positive and negative words. I find strong evidence for the positive effect on virality of the emotions anger, anxiety and surprise in all three social media. Further, Facebook users exhibit partially another sharing behavior than users on Twitter and Google+.

These ambiguous results suggest refraining from simple generalization: The drivers and moderators for content diffusion might depend on the context, the communication medium, and sender’s traits and might also be different for different cultures. This study provides then directions for future research on diffusion processes in different communication media.

[21] I also tested whether the quadratic term of emotionality has an effect on content’s virality, but the results were insignificant.

	# Likes	# Tweets	# Plus-ones	Most emailed	Positivity	Emotionality	Anger	Anxiety	Awe	Sadness	Surprise	Utility	Interest	Coded	# Words	Time of day	Complexity	Top featured	In first position	In teaser	Hours on homepage	Hours in top	Hours first position	Hours in teaser
# Tweets	0.55*	1																						
# Plus-ones	0.61*	0.71*	1																					
Most emailed	0.27*	0.27*	0.35*	1																				
Positivity	0.01	0.01	0.02	0.03*	1.00																			
Emotionality	0.02*	0	0	0.01	-0.08	1																		
Anger	0	-0.01	-0.01	0	-0.33*	0.06	1																	
Anxiety	0	-0.01	-0.01	0	-0.33*	0.06	0.43*	1																
Awe	-0.01	-0.01*	-0.01	0	0.20*	0.04	-0.27*	-0.11*	1															
Sadness	0	-0.01	-0.01	0	-0.35*	0.11*	0.35*	0.49*	-0.10	1														
Surprise	0	-0.01	0	0	0.03	-0.09	0.03	0.11	0.21*	0.05	1													
Utility	-0.01	-0.01	0	0	0.23*	-0.00	-0.09	-0.10	0.08	-0.13	-0.02*	1												
Interest	0	-0.01	0	0	-0.05	0.03	0.30 *	0.35*	-0.01	0.14*	0.23*	0.01	1											
Coded	-0.01	-0.02*	-0.01	0	0	-0.01	0.89*	0.89*	0.9*	0.88*	0.93*	0.87*	0.96*	1										
# Words	0.06*	0.15*	0.12*	0.11*	0.1*	0.08*	-0.03*	-0.03*	-0.03*	-0.03*	-0.04*	-0.03*	-0.03*	-0.04*	1									
Time of day	0.02*	0	0.05*	0.06*	0.04*	-0.01	0.01	0.02*	0.02*	0.01	0.01	0.01*	0.02*	0.01*	0.09*	1								
Complexity	0.03*	-0.08*	-0.02	0.03*	0.24*	0.17*	-0.02*	-0.02*	0.01	-0.01	0	0	-0.01	0	0.15*	0.03*	1							
Released as top featured	0.1*	0.26*	0.12*	0.09*	-0.02*	0.05*	-0.01	-0.01	-0.01*	-0.01	-0.01	-0.01	-0.01	-0.01	0.15*	-0.06*	0.04*	1						
Released on first position	0.11*	0.22*	0.14*	0.13*	0.07*	0.03*	-0.01	-0.01	0	-0.01	0	0	0	-0.01	0.19*	-0.03*	0.09*	0.45*	1					
Released as teaser	0.06*	0.17*	0.07*	0.02*	-0.04*	0.01	0	0	0	0	0	-0.01	0	0	0.08*	-0.04*	-0.05*	-0.11*	0.12*	1				
Hours on landing page	0.04*	0.02*	0.08*	0.04*	0.04*	0	0	0	0	0	0.01	0.01	0	0	0.08*	0.05*	0.05*	0.05*	0.14*	-0.01*	1			
Hours as top featured	0.03*	0.03*	0.05*	0.01	0	0.01*	0	0	0	0	0	0	0	0	0.04*	0.01	0.02*	0.11*	0.06*	-0.01	0.62*	1		
Hours as first position	0.08*	0.11*	0.09*	0.13	0.06*	0	-0.01	0	0	0	0.01	0.01	0	0	0.17*	-0.06*	0.1*	0.2*	0.44*	0.03*	0.27*	0.11*	1	
Hours as teaser	0.05*	0.12*	0.04*	0.02*	-0.02*	0	0	0.01	-0.01	0	0	0	0	0	0.04*	-0.05*	-0.02*	-0.06*	0.07*	0.52*	0	-0.01	0.04*	1

Note: * $p < 0.05$

Table 35. Correlation matrix

	(1) Most emailed	(2) # Likes	(3) # Tweets	(4) # Plus-ones	(5) Most emailed	(6) # Likes	(7) # Tweets	(8) # Plus-ones	(9) Most emailed	(10) # Likes	(11) # Tweets	(12) # Plus-ones
Positivity	2.544*	0.174	0.0670+	0.232+	0.082^{+}	0.030***	0.001	-0.009	0.094*	0.072***	0.009***	0.004
	(1.002)	(0.112)	(0.0364)	(0.129)	(0.043)	(0.001)	(0.001)	(0.006)	(0.047)	(0.001)	(0.001)	(0.007)
Positivity^2									-0.006	-0.032***	-1.157***	-0.013***
									(0.010)	(0.000)	(0.015)	(0.001)
Emotionality	1.022	0.109	-0.0364	0.212+	0.113**	0.051***	-0.000	0.031***	0.126**	0.112***	0.017***	0.056***
	(0.672)	(0.097)	(0.0322)	(0.113)	(0.040)	(0.001)	(0.001)	(0.006)	(0.045)	(0.001)	(0.001)	(0.006)
Anger	0.061	0.101***	0.00980	-0.016	0.125	0.060***	0.023***	0.062***	0.125	0.059***	0.023***	0.061***
	(0.123)	(0.031)	(0.0110)	(0.040)	(0.095)	(0.001)	(0.003)	(0.017)	(0.095)	(0.001)	(0.003)	(0.017)
Anxiety	-0.123	-0.036	-0.00848	0.023	-0.151	-0.021***	-0.012***	-0.050***	-0.151	-0.020***	-0.013***	-0.050***
	(0.147)	(0.033)	(0.0120)	(0.037)	(0.093)	(0.001)	(0.003)	(0.014)	(0.093)	(0.001)	(0.003)	(0.014)
Awe	-0.343^{+}	0.058*	0.00268	0.006	-0.109	-0.033***	0.008**	0.011	-0.110	-0.034***	0.008**	0.010
	(0.192)	(0.028)	(0.00920)	(0.032)	(0.111)	(0.001)	(0.003)	(0.015)	(0.111)	(0.001)	(0.003)	(0.015)
Sadness	0.365	0.046^{+}	0.00651	0.001	0.075	0.009***	0.001	-0.017	0.074	0.009***	0.001	-0.017
	(0.226)	(0.024)	(0.0112)	(0.041)	(0.091)	(0.001)	(0.003)	(0.019)	(0.091)	(0.001)	(0.003)	(0.019)
Surprise	0.150	0.003	-0.0123	0.100**	0.058	0.016***	0.007*	0.099***	0.059	0.020***	0.008*	0.102***
	(0.179)	(0.032)	(0.0118)	(0.038)	(0.119)	(0.002)	(0.003)	(0.018)	(0.120)	(0.002)	(0.003)	(0.018)
Utility	0.156	0.023	-0.00467	0.033	0.032	-0.046***	0.002	0.041***	0.032	-0.046***	0.002	0.042***
	(0.161)	(0.027)	(0.00821)	(0.032)	(0.068)	(0.001)	(0.002)	(0.010)	(0.068)	(0.001)	(0.002)	(0.010)
Interest	0.129	0.137**	0.0597***	0.174**	-0.022	-0.023***	0.027***	0.098***	-0.024	-0.031***	0.026***	0.096***
	(0.201)	(0.050)	(0.0162)	(0.063)	(0.168)	(0.002)	(0.005)	(0.028)	(0.168)	(0.002)	(0.005)	(0.028)
Coded					-0.312	0.219***	-0.515***	-1.948***	-0.301	0.265***	-0.506***	-1.952***
					(1.721)	(0.025)	(0.051)	(0.270)	(1.72)	(0.025)	(0.051)	(0.270)
In top	4.151*	1.404***	0.370***	0.468	0.737***	0.773***	0.453***	0.594***	0.735***	0.765***	0.450***	0.589***
	(2.038)	(0.350)	(0.096)	(0.289)	(0.092)	(0.001)	(0.003)	(0.014)	(0.092)	(0.001)	(0.003)	(0.014)
In first position	1.362	0.726**	0.165*	0.195	0.471***	0.322***	0.112***	0.234***	0.471***	0.316***	0.111***	0.233***
	(1.708)	(0.254)	(0.084)	(0.260)	(0.099)	(0.001)	(0.003)	(0.014)	(0.099)	(0.001)	(0.003)	(0.014)
In teaser		0.503	0.417**	-1.674**	0.791***	1.083***	0.572***	0.820***	0.790***	1.078***	0.570***	0.821***
		(0.439)	(0.143)	(0.612)	(0.192)	(0.002)	(0.005)	(0.025)	(0.192)	(0.002)	(0.005)	(0.025)
# Words x 10^{-3}	0.055	-0.994**	0.132	-0.769^{+}	0.298***	0.010***	0.071***	0.175***	0.293***	-0.016***	0.063***	0.166***
	(5.283)	(0.383)	(0.141)	(0.420)	(0.070)	(0.001)	(0.002)	(0.010)	(0.071)	(0.001)	(0.002)	(0.010)
Complexity	0.093^{+}	-0.000	-0.003	-0.009	0.010**	0.010***	-0.002***	0.010^{+}	0.010**	0.010***	-0.002***	0.010^{+}
	(0.052)	(0.010)	(0.003)	(0.010)	(0.003)	(0.000)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.001)
Male author	-0.365	-0.171	0.244	-0.369	0.029	0.057***	0.048***	-0.085***	0.030	0.059***	0.049***	-0.083***
	(1.508)	(0.367)	(0.169)	(0.377)	(0.111)	(0.002)	(0.004)	(0.019)	(0.111)	(0.002)	(0.004)	(0.019)
News agency	-2.198	0.170	0.033	0.352	-0.861***	-0.178***	-0.128***	-0.341***	-0.856***	-0.154***	-0.121***	-0.331***
	(3.672)	(0.287)	(0.094)	(0.319)	(0.089)	(0.001)	(0.003)	(0.014)	(0.089)	(0.001)	(0.003)	(0.014)
Time-of-day	0.005	0.651**	0.084	0.611**	0.728***	0.210***	0.006**	0.234***	0.726***	0.203***	0.005*	0.233***
	(0.024)	(0.206)	(0.075)	(0.227)	(0.100)	(0.001)	(0.002)	(0.013)	(0.100)	(0.001)	(0.002)	(0.013)
Web timing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Release timing	Yes	Yes	Yes	Yes		Fixed effects				Fixed effects		
Constant	-16.11*	1.232	2.746***	-2.501*								
	(7.767)	(1.013)	(0.307)	(1.177)								
Ln alpha		0.450***	-1.507***	-0.290								
		(0.066)	(0.086)	(0.187)								
N	311	311	311	186	21775	21843	21843	9246	21775	21843	21843	9246
Pseudo R^2	0.556	0.061	0.068	0.114	0.219				0.219			
Wald χ^2	39.25*	454.1***	533.5****		1491.0***	1814270.2***	162003.7***	17902.9***	1491.4***	1842037.4***	162514.6***	17921.2***

Robust standard errors in parentheses $^{+}$ $p < .10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 36. Estimation results

7 SUMMARY, IMPLICATIONS, AND OUTLOOK

7.1 Summary

This dissertation addresses the social sharing design. First, I suggest a new conceptual framework for studying social sharing processes. Then I synthesize the current status of knowledge along the components of social sharing: responses, sender, receiver, message, content and sharing mechanisms as well as other contextual factors. The analysis of the different components shows various voids where empirical research is needed. Whereas our knowledge on the drivers on social sharing processes with respect to the sender, receiver and message characteristics are quite comprehensive, the effects of communication context characteristics especially of the sharing mechanisms are scarce. With the following empirical studies, I then address some of the identified research gaps. Three empirical projects investigate the effects of five different sharing mechanism characteristics, namely sender's control over the sharing process, preservation of user's privacy, symbolic expression of self-focus, anonymity and payment of incentives. Two studies center on how content's valence and controversy might affect social sharing processes.

The first empirical project investigates the effects of user control over the sharing process, preservation of user's privacy, and symbolic expressions of self-focus. The results from a laboratory experiment and two field studies show that sharing mechanisms that allow greater control over the sharing process, those that aim to preserve the user's privacy, and those that express a self-focus negatively affect content sharing. Although no interaction effect emerged between sharing mechanisms that express self-focus with the valence of content, the investigation reveals that extroverted individuals make particular use of such mechanisms to express their opinions and feelings.

The second research project investigates how the systems which facilitate users' interaction with media sites and which allow the non-disclosure of the users' identity impact social sharing. Using a two-month sample of articles published on one of European's largest news sites *Spiegel Online*, I find that articles related to controversial topics such as religion, politics, and money are less likely to be shared on Facebook, whereas they are actively discussed on discussion boards under pseudonyms. I find a U-shaped relationship between controversy and the ratio of number comments and the number of Likes on Facebook.

The third research project analyses how the payment of incentives influences the social sharing. For that purpose, I analyse data from three field experiments. The results show that payment of incentives might stimulate social sharing in terms of writing reviews. Moreover, paid customers write less positive, less emotional, but longer and more factual reviews.

The last study focuses on the social sharing design from the content perspective and constitutes a replication of Berger and Milkman (2012) who find that an online content's virality is positively associated with its positivity and emotionality, as well as with emotions anger, awe and is negatively related to the emotions anxiety and sadness. I replicate their study for four different communication media. I find strong evidence for the effects of emotionality, anger and anxiety and an inverted U-shape relation between content's positive sentiment and its virality.

7.2 Implications

Previous research on diffusion processes mainly focuses on identifying influential persons, rather than the impacts of sharing mechanism designs, content characteristics, and other contextual factors. These studies thus contribute to research on social sharing in several ways, particularly in relation to the evolving stream of research on the effects of sharing mechanisms and their interactions with sender and content characteristics. By applying the framework proposed by Markus and Silver (2008) to characterize sharing mechanism features, this study contributes also to research into ICT use and exploitation. Social media have become an important channel that can be used by marketers to spread content easily and affordably. Examining the effects of sharing mechanisms and content itself could contribute to our understanding of different outcomes, extent and patterns of social sharing, enabling marketers to direct their strategies. My dissertation contributes thus by offering the first in-depth and integrated understanding of the impact of sharing mechanism and content design on social sharing and provides a new theoretical perspective for the social sharing literature by linking particularly sharing mechanisms and social sharing.

The findings demonstrate that the design of content and sharing mechanisms is not a trivial task and even subtle differences in visual presentation, such as display of different words ("like" or "recommend") affect social sharing behavior. The results also should help marketers write more viral content; for example, articles featuring high levels of anger and awe are often shared on Facebook, whereas those marked mainly by their practical utility are less frequently shared. Because journalistic integrity might prevent authors from deliberately crafting content to go viral, the findings suggest that social media planners might be the best candidates to leverage diffusion processes in social media through deliberate designs of sharing mechanisms. As shown in the second research project content with high level of controversy is less appropriate to discuss on communication media that reveal sender's and receiver's identities.

7.3 Outlook

Previous research on content sharing analyzes isolated aspects of different key components; an integrated approach could effectively account for possible interaction effects among sender and receiver characteristics, their relationships, content and sharing mechanism characteristics, and other contextual factors such as attention competition. Studies by Schulze et al. (2014) and Berger and colleagues as well as the present study represent pioneers in revealing the interactions across different components of social sharing processes. Although this dissertation analyzes several sharing mechanism and content characteristics, many research questions remain still open.

Moreover, previous studies mostly focus on the benefits gained from social sharing occurrences. As mentioned several times in this dissertation, the willingness to engage in social sharing constitutes a benefit-cost calculus of senders and receivers. Future studies could then further develop the ideas first addressed in empirical studies by Jin and Huang (2014) and Wirtz et al. (2013) who investigate the effects of social costs associated with social sharing. This intersection of psychology, sociology, and information systems research thus provides many promising new research opportunities, with high value for business practice.

8 APPENDIX

8.1 Appendix Section 3

Laboratory experiment instructions

Recruiting phase. Thank you for participating in our study. You must accomplish some tasks on a PC, then answer questions about your personality. The study will last between 20 and 30 minutes. All data will be treated confidentially.

Experimental phase. Different online social networks offer their users an opportunity to share content with friends and acquaintances. This study investigates which kind of content is shared on Facebook, a famous social network. There are no right or wrong answers. This study is about your personal opinions. We promise that all data will be treated confidentially and used solely for scientific purposes.

Personal trait measures

Variable	Coding	English	German
Need to belong (Leary et al. 2004)	(-)	If other people don't seem to accept me, I do not let it bother me.	Es kümmert mich nicht, wenn andere Leute mich nicht akzeptieren.
	(-)	I try not to do things that will make other people avoid or reject me.	Ich versuche Handlungen zu vermeiden, weswegen andere Leute mich ablehnen oder zurückweisen werden.
	(-)	I seldom worry about whether other people care about me.	Ich mache mir selten Sorgen, ob andere Leute sich für mich interessieren.
		I need to feel that there are people I can turn to in times of need.	Ich brauche das Gefühl, dass es Leute gibt, an welche ich mich wenden kann, wenn ich es brauche.
		I want other people to accept me.	Ich möchte, dass andere Leute mich akzeptieren.
		I do not like being alone.	Ich bin nicht gerne alleine.
	(-)	Being apart from my friends for long periods of time does not bother me.	Es macht mir nicht aus, für eine lange Zeit weg von meinen Freunden zu sein.
		I have a strong "need to belong."	Ich habe ein starkes Bedürfnis, „ dazu zu gehören".
		It bothers me a great deal when I am not included in other people's plans.	Es beschäftigt mich sehr, wenn andere Leute mich nicht in ihre Pläne einbeziehen.
		My feelings are easily hurt when I feel that others do not accept me.	Meine Gefühle sind schnell verletzt, wenn ich das Gefühl habe, dass andere Leute mich nicht akzeptieren.
Extraversion Neo-FFI (Costa and McCrae 1992)		Feel comfortable around people.	Ich fühle mich wohl unter Leuten.
		Make friends easily.	Ich lerne leicht Freunde kennen.
		Am skilled in handling social situations.	Ich kann gut verschiedene soziale Situationen meistern.
		Am the life of the party.	Ich bin eine Stimmungskanone.
		Know how to captivate people.	Ich weiß wie man Leute fasziniert.
		Have little to say.	Ich habe wenig zu erzählen.
	(-)	Keep in the background.	Ich halte mich im Hintergrund.
	(-)	Would describe my experiences as somewhat dull.	Ich würde meine Erfahrungen als uninteressant bezeichnen.
	(-)	Don't like to draw attention to myself.	Ich mag es nicht, die Aufmerksamkeit auf mich zu ziehen.
Altruism Neo-FFI (Costa and McCrae 1992)		Make people feel welcome.	Ich mag, dass Leute sich wohl fühlen.
		Anticipate the needs of others.	Ich behandle die Bedürfnisse anderer Leute zuvorkommend.
		Love to help others.	Ich mag es anderen Leuten zu helfen.
		Am concerned about others.	Ich mache mir um andere Leute Sorgen.
		Have a good word for everyone.	Ich rede gut über andere Leute.
	(-)	Look down on others.	Ich sehe auf andere hinab.
	(-)	Am indifferent to the feelings of others.	Die Gefühle von anderen sind mir egal.
	(-)	Make people feel uncomfortable.	Durch mich fühlen sich Leute unwohl.
	(-)	Turn my back on others.	Ich lasse andere im Stich.
	(-)	Take no time for others.	Ich nehme mir keine Zeit für andere.

Table 37. Measures of need to belong, extraversion, and altruism

Variable	(1)N_Likes	(2)N_Likes	(3) N_Likes	(4)N_Likes	(5)N_Likes	(6)N_Likes	(7)N_Likes
High_control	-1.349***	-1.090***	-1.047***	-0.901***	-0.777***	-0.720***	-0.439*
	(-7.65)	(-6.07)	(-6.06)	(-4.51)	(-3.82)	(-3.43)	(-1.97)
Self_focus	-1.212***	-1.087***	-1.039***	-1.155***	-0.889***	-0.817***	-0.584**
	(-5.99)	(-5.40)	(-5.11)	(-5.49)	(-3.92)	(-3.51)	(-2.59)
Privacy	-0.540**	-0.518**	-0.492**	-0.792***	-0.904***	-0.882***	-0.676***
	(-3.16)	(-3.14)	(-2.88)	(-5.78)	(-7.00)	(-6.74)	(-5.70)
Positivity[a]		0.0121	0.0249	0.129+	0.125	0.133+	0.120
		(0.18)	(0.38)	(1.66)	(1.57)	(1.68)	(1.63)
Emotionality[a]		-0.407***	-0.357***	-0.365***	-0.286***	-0.303***	-0.306***
		(-5.53)	(-4.93)	(-6.10)	(-5.07)	(-5.05)	(-5.00)
Self_focus Positivity*[a]		0.0159	0.0449	-0.0545	-0.0783	-0.0862	-0.0608
		(0.18)	(0.53)	(-0.53)	(-0.77)	(-0.83)	(-0.66)
Anger[a]			0.303***	0.308***	0.321***	0.318***	0.343***
			(4.14)	(4.97)	(5.26)	(5.31)	(6.10)
Awe[a]			0.0840	0.156*	0.136*	0.130+	0.164**
			(1.24)	(2.22)	(2.04)	(1.93)	(2.67)
Sadness[a]			-0.127+	-0.0869	0.00599	0.00915	-0.0406
			(-1.91)	(-1.15)	(0.07)	(0.10)	(-0.68)
Anxiety[a]			-0.0198	-0.0271	-0.0563	-0.0515	-0.0848
			(-0.28)	(-0.37)	(-0.81)	(-0.74)	(-1.39)
Interest[a]			0.170*	0.239***	0.191**	0.200***	0.200***
			(2.53)	(4.11)	(3.19)	(3.35)	(3.78)
Surprise[a]			0.00384	-0.0258	0.0502	0.0531	0.0626
			(0.05)	(-0.38)	(0.83)	(0.88)	(1.14)
Pract_Utility[a]			-0.0708	-0.189***	-0.181**	-0.185**	-0.153**
			(-1.20)	(-3.44)	(-3.15)	(-3.19)	(-2.85)
D_cars				-1.400***	-0.992*	-1.009*	-0.945*
				(-3.79)	(-2.51)	(-2.49)	(-2.53)
D_career				1.119**	0.932*	0.884*	0.810*
				(2.60)	(2.20)	(2.06)	(2.17)
D_society				-0.405	-0.0865	-0.101	-0.179
				(-1.21)	(-0.24)	(-0.28)	(-0.58)
D_lifestyle				0.779	0.614	0.641	0.441
				(1.19)	(1.23)	(1.26)	(1.00)
D_politics				-0.101	0.0378	0.0487	0.00369
				(-0.32)	(0.13)	(0.16)	(0.01)
D_localnews				1.020	1.558+	1.597+	1.446+
				(1.41)	(1.89)	(1.88)	(1.75)
D_travel				0.347	0.419	0.350	0.288
				(0.90)	(1.12)	(0.92)	(0.76)
D_humor				-0.0213	-0.189	-0.119	-0.151
				(-0.04)	(-0.31)	(-0.19)	(-0.25)
D_sports				-1.920***	-1.682***	-1.702***	-1.788***
				(-5.89)	(-5.44)	(-5.38)	(-6.24)
D_technology				0.288	0.332	0.319	0.238
				(0.67)	(0.87)	(0.82)	(0.64)
D_business				-0.724*	-0.574+	-0.550+	-0.620*
				(-2.41)	(-1.90)	(-1.79)	(-2.21)
D_science				0.108	0.440	0.454	0.505
				(0.28)	(1.04)	(1.06)	(1.16)
D_agency					-0.980***	-0.942***	-0.968***
					(-7.19)	(-6.86)	(-7.30)
D_AuthFemale					-0.0321	-0.0101	0.0352
					(-0.17)	(-0.05)	(0.19)
AuthFame					0.0000778**	0.0000820**	0.0000604*
					(2.63)	(2.81)	(2.57)
Complexity					-0.0161***	-0.0162***	-0.0143***
					(-3.93)	(-3.93)	(-3.81)
N_images						0.0160*	0.0137*
						(2.31)	(2.31)

N_videos						0.0288	-0.0323
						(0.24)	(-0.29)
D_position							0.457**
							(3.18)
N_articles							-0.000839*
							(-2.41)
Reach							-0.00326
							(-1.09)
t							0.000890
							(1.15)
D_hour03							-0.122
							(-0.25)
D_hour06							-0.752^{+}
							(-1.80)
D_hour09							0.756**
							(2.84)
D_hour12							0.477*
							(2.10)
D_hour15							0.362
							(1.52)
D_hour18							-0.0260
							(-0.12)
D_hour21							0.325
							(1.32)
D_weekend							-0.499^{+}
							(-1.85)
Constant	5.123***	4.832***	4.713***	5.299***	6.431***	6.269***	7.080***
	(21.03)	(19.52)	(19.54)	(13.20)	(12.55)	(11.75)	(7.66)
Ln alpha	1.659***	1.627***	1.603***	1.466***	1.390***	1.387***	1.353***
	(57.76)	(54.33)	(49.94)	(47.83)	(43.43)	(42.73)	(45.12)
N	4278	4278	4278	4278	4278	4278	4278
pseudo R^2	0.003	0.008	0.011	0.031	0.041	0.042	0.046
LL (full model)	-14954.9	-14886.7	-14836.6	-14547.9	-14387.7	-14381.6	-14311.4
LL (constant only)	-15006.4	-15006.4	-15006.4	-15006.4	-15006.4	-15006.4	-15006.4
Wald χ^2 tests	62.63***	123.4***	155.8***	433.3***	688.7***	701.3v	965.4***

Notes: *t* statistics in parentheses. $^{+}$ $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$. ^{a} Standardized variables.

Table 38. Full model for study 1

Variable	(1) IntLike	(2) IntLike	(3) IntLike	(4) IntLike	(5) IntLike	(6) IntLike
High_control	-0.792***	-0.809***	-0.846***	-0.784***	-0.734***	-0.588**
	(-5.55)	(-5.63)	(-5.88)	(-4.64)	(-4.24)	(-2.90)
Self_focus	-0.0875	-0.0696	-0.0663	0.00732	-1.354*	-2.093**
	(-0.64)	(-0.50)	(-0.47)	(0.05)	(-2.17)	(-3.12)
Positivity[a]		-0.0295	-3.965**	-4.290***	-4.284***	-4.433***
		(-0.23)	(-3.27)	(-3.45)	(-3.43)	(-3.53)
Emotionality[a]		0.313**	-4.697***	-5.074***	-5.073***	-5.239***
		(2.59)	(-3.45)	(-3.63)	(-3.62)	(-3.71)
*Self_focus**		-0.0879	-0.0902	-0.0852	-0.0830	-0.0650
Positivity[a]		(-0.76)	(-0.75)	(-0.71)	(-0.69)	(-0.54)
Anger[a]			-7.198***	-7.750***	-7.774***	-8.061***
			(-4.00)	(-4.19)	(-4.19)	(-4.30)
Awe[a]			5.282***	5.681***	5.699***	5.899***
			(4.06)	(4.24)	(4.25)	(4.36)
Interest[a]			1.438***	1.528***	1.541***	1.593***
			(5.94)	(6.32)	(6.38)	(6.47)
Pract_Utility[a]			1.049***	1.128***	1.128***	1.183***
			(3.44)	(3.57)	(3.56)	(3.69)
Surprise[a]			-0.588***	-0.622***	-0.627***	-0.651***
			(-5.17)	(-5.37)	(-5.38)	(-5.50)
Sadness[a]			omitted			
Anxiety[a]			omitted			
Age				-0.159***	-0.177***	-0.178***
				(-4.71)	(-5.02)	(-4.64)
Female				-0.0925	-0.0280	0.203
				(-0.67)	(-0.19)	(1.03)
D_highschool				omitted		
D_bachelor				0.352*	0.332^{+}	0.406*
				(2.07)	(1.92)	(2.15)
D_master				1.586***	1.742***	1.769***
				(4.33)	(4.46)	(4.31)
D_friends100				omitted		
D_friends200				-1.338***	-1.302***	-1.262***
				(-5.76)	(-5.28)	(-5.02)
D_friends300				-0.763**	-0.815**	-0.883***
				(-3.24)	(-3.28)	(-3.67)
D_friends400				-0.768**	-0.803**	-0.625*
				(-3.20)	(-3.18)	(-2.55)
D_friends500				-2.186***	-2.404***	-2.342***
				(-5.98)	(-5.90)	(-5.50)
D_friendsmore500				-1.197***	-1.346***	-0.831**
				(-4.37)	(-4.54)	(-2.67)
D_Never				omitted		
D_As_good_as_never				-0.0201	-0.0964	-0.335
				(-0.08)	(-0.41)	(-1.28)
D_Once_month				0.564*	0.475^{+}	-0.00787
				(2.02)	(1.67)	(-0.02)
D_Once_week				0.449^{+}	0.197	0.0346
				(1.68)	(0.69)	(0.11)
D_Several_ times_week				0.550^{+}	0.373	-0.0118
				(1.87)	(1.21)	(-0.04)
D_Once_day				1.383**	1.378**	1.074*
				(3.27)	(3.13)	(2.29)
D_Several_times_day				0.740	0.381	-0.237
				(1.57)	(0.79)	(-0.43)
Need_to_Belong					0.0242	0.0703
					(0.29)	(0.78)
Altruism					-0.195	0.0122
					(-1.54)	(0.09)

Extraversion					0.111	0.0373
					(1.15)	(0.36)
*Self_focus**					0.294*	0.453***
Extraversion						
Reading interests dummies					(2.35)	(3.29)
D_cars						-0.420*
						(-2.13)
D_career						0.142
						(0.98)
D_society						0.286^{+}
						(1.94)
D_humor						-0.943***
						(-5.92)
D_culture						-0.0938
						(-0.62)
D_sports						-0.0138
						(-0.11)
D_lifestyle						0.237
						(1.39)
D_localnews						0.179
						(0.93)
D_politics						-0.324*
						(-2.04)
D_travel						-0.287^{+}
						(-1.77)
D_technology						0.695***
						(3.68)
D_business						-0.152
						(-0.81)
D_science						0.0450
						(0.25)
N	992	992	992	992	992	992
pseudo R^2	0.011	0.025	0.045	0.076	0.080	0.097
LL (full model)	-1692.2	-1669.0	-1634.8	-1581.6	-1575.0	-1544.6
LL (constant only)	-1711.2	-1711.2	-1711.2	-1711.2	-1711.2	-1711.2
Wald χ^2- test	36.62***	83.21***	138.3***	249.1***	268.1***	315.4***

Notes: *t* statistics in parentheses. $^{+}$ $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$. ^{a} Standardized variables.

Table 39. Full model for study 2, laboratory experiment

Variable	*N_Likes*
Privacy	-0.349*
	(-2.39)
Paywall	-0.901**
	(-2.65)
D_weekend	-0.241***
	(-3.86)
t	5.14e-4
	(1.25)
D_Feb	-0.340***
	(-3.42)
D_Mar	-0.176^{+}
	(-1.80)
D_Apr	-0.0910
	(-0.69)
D_May	-0.139
	(-1.48)
D_June	-0.180
	(-1.08)
D_July	-1.008***
	(-6.59)
D_Aug	-0.966***
	(-6.74)
D_Sept	-0.960***
	(-5.57)
D_Oct	-0.310*
	(-2.28)
D_Nov	-0.273^{+}
	(-1.65)
D_Dec	-0.288**
	(-2.63)
Constant	10.27***
	(108.11)
Ln alpha	-0.276***
	(-3.41)
N	699
pseudo R^2	0.007

Notes: *t* statistics in parentheses. $^{+}$ $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 40. Full model for study 3

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