Three Essays on Understanding Mobile Consumer Behavior: Business Models, Perceptions, and Features

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Summary

For about a decade, consumers have been carrying the Internet in their pockets. The rapid penetration of modern smartphones has meant that more than two-thirds of the people in the West can access and use online resources, anytime and anywhere. Consumers also can communicate and share their consumption experiences instantaneously. Platforms reach users for time-critical events through highly personal communication channels, in the sense that smartphones serve as constant companions. Many mobile applications and their basic services and contents also are available for free. The digital and mobile worlds thus are changing the very means of communication, suggesting the powerful need for marketing research and practice to find the opportunities and meet the challenges of the mobile Internet. In particular, scientific investigations are required to describe new business models in the free e-service industry and the consumer behavior affected by mobile features. This thesis examines these topics in three essays.

Study 1 considers business models that offer their services without charge. Offering services for free is symptomatic of not only mobile apps (90% of all apps are available for free) but the digital economy in general. For companies offering free e-services, this situation raises several important questions, in that, without any access device restrictions, how do customers of free e-services contribute value without paying? What are the nature and dynamics of nonmonetary value contributions by nonpaying customers? With a literature review and interviews with senior executives of free e-service providers, Study 1 presents a comprehensive overview of nonmonetary value contributions in the free e-service sector, including word of mouth, co-production, and network effects. Moreover, adding attention and data into this framework reveals two further aspects that have not been addressed in prior customer value research. By putting the findings in the context of the existing literature on customer value and customer engagement, this study sheds light on the complex processes of value creation in the emerging e-service sector, while advancing marketing and service research in general.

Study 2 deepens the findings from the first study; specifically, the focus is on the way that mobile users co-produce content and how this contribution is perceived by recipients in the network. With field data and a scenario experiment, this study demonstrates that recipients appreciate mobile-generated customer reviews fundamentally differently from other reviews. In particular, they discount the helpfulness of mobile reviews, due to their text-specific content and style particularities. The very fact that a review has been identified as written on a mobile device also lowers recipients' perceptions of its value. Recipients use information about the device as a source cue to assess their compatibility with the review contribution channel. If they perceive themselves as compatible with the method used to generate the review (mobile or non-mobile), recipients regard the review as more helpful, because they attribute the review to the quality of the reviewed subject. If they perceive it as incompatible though, recipients assume that the review reflects the personal dispositions of the reviewer and discount its helpfulness.

Finally, Study 3 takes up the attention and cross-market network effects in a mobile setting; these were two nonmonetary dimensions identified by Study 1. Platform providers should develop measures to draw the attention of nonpaying customers to the offers of their paying customers. One attention-grabbing mobile-specific feature is push notifications to the device, which provide information about temporally or spatially relevant events. More concretely, Study 3 investigates how mobile push notifications remind users of upcoming deadlines in online auctions and therefore improve late bidding success. Late bidding is a prevalent strategy, in which bidders submit their bids at the very end of an online auction. This research uses field data about an online auction platform to demonstrate that late bidders use these mobile push notifications more frequently than do bidders with different bidding patterns. Within the group of late bidders, the chance to win an auction increases with their use of push notifications. After a mobile push notification, late bidders submit bids through mobile devices but also through non-mobile channels. Less experienced late bidders also benefit from push notifications, which increase their chances of success.

In summary, this dissertation contributes to an enhanced understanding of mobile consumer behavior by using various methods, including qualitative interviews, field observations, and online experiments. From a theoretical perspective, it contributes to current knowledge about nonmonetary costumer value contributions in general

and their role in mobile settings in particular. This thesis highlights the role of mobile devices in co-production and perceptions of co-produced content. It also reveals how mobile-specific interactive features, like push notifications, affect late bidding efficiency. Therefore, it specifies the role of mobile devices in cross-market effects, in that they enable the platform to direct the relationship between buyers and sellers. The insights presented herein encourage managers to reevaluate their current practices, think about whether they should label co-produced content as generated through a mobile channel or not, and contemplate whether to develop mobile push notifications as helpful features for users (not as intrusive marketing messages).

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List of Abbreviations

B2C.....Business-to-Consumer
C2C.....Consumer-to-Consumer
CEB.....Customer Engagement Behavior
CET.....Central European Time
CEV.....Customer Engagement Value
CI.....Confidence Interval
CLV.....Customer Lifetime Value
Coeff.....Coefficient
CRM.....Customer Relationship Management
CRV.....Customer Referral Value
GPS.....Global Positioning System
IMC.....Instruction Manipulation Check
KPI.....Key Performance Indicator
LIWC.....Linguistic Inquiry and Word Count
LLCI.....Lower-Level Confidence Interval
M.....Mean
NMCVC.....Nonmonetary Customer Value Contribution
PC.....Personal Computer
SD.....Standard Deviation
SE.....Standard Error
UGC.....User-Generated Content
ULCI.....Upper-Level Confidence Interval
WOM.....Word of Mouth

1 Introduction

1.1 General Motivation and Background

The mobile Internet is omnipresent, in a dual sense of the word: the high and still growing penetration rates of more than 67% in Western Europe and 75% in North America estimated in 2015 (eMarketer, 2015), as well as the full spectrum of ubiquity they entail, spanning continuity, immediacy, portability, and searchability (Okazaki & Mendez, 2013). The opportunities and challenges of mobile commerce, available "anywhere, anytime," have been outlined in early research (Balasubramanian, Peterson, & Jarvenpaa, 2002). Yet a breakthrough came with the introduction and subsequent distributions of modern smartphones (led by the iPhone in 2007), which support easy-to-use access to Internet resources (Okazaki & Mendez, 2013). Smartphones are pocket-sized, always on, always connected, and controlled with a single finger, so they provide powerful spatial and temporal advantages in comparison with conventional devices such as PCs or laptops (Wang, Malthouse, & Krishnamurthi, 2015).

In turn, mobile devices have altered the challenges for business and marketers in such drastic ways that there is even talk of the "second Internet revolution" (Forrester, 2013). Three main challenges then arise for marketing research and marketing managers in the mobile (and digital, more generally) economy: (1) the establishment of new business models (Appel, Libai, & Muller, 2015), (2) the question of new marketing and communication channels (Hennig-Thurau et al., 2010), and (3) ways to cope with big data using analytical approaches (Hofacker, Malthouse, & Sultan, 2016).

First, recent research notes the emerging role of mobile shopping for retailing (Wang et al., 2015), yet an even more prevalent digital business model entails offering services for free (Anderson, 2009; Bryce, Dyer, & Hatch, 2011). More than 90% of mobile app downloads impose no costs on users (Gartner, 2013). The monetization of free mobile apps thus remains an emerging question (Appel et al., 2015).

Second, new media channels enable customers to interact with both firms and other customers, such as through online consumer reviews, and they move beyond classical, one-way push marketing measures (Shankar & Malthouse, 2007). A parallel shift within the push–pull marketing dichotomy notes the move from firm-initiated to customer-initiated contacts (Wiesel, Pauwels, & Arts, 2011). Because mobile devices are consumers' constant companions, they come to feel like personal accessories (Shankar, Venkatesh, Hofacker, & Naik, 2010), such that commercial messages are perceived as very intrusive (Dickinger & Kleijnen, 2008). Thus, highly individualized communication controlled by the consumer is necessary in mobile channels (Bacile, Ye, & Swilley, 2014). Finally, little is known about the role of mobile devices or their interactions with other devices in omnichannel marketing strategies (Grewal, Bart, Spann, & Zubcsek, 2016).

Third, in the digital world, customers leave big digital footprints. All customers' clicks and visits on websites can be tracked and stored. Because mobile devices provide additional information about their users, such as location details, firms need to strengthen their data storage and analytical capacities to leverage the effectiveness of any time- or location-sensitive mobile ads and services they issue (Grewal et al., 2016; Hofacker et al., 2016). Limitless unstructured data, such as text produced in social media (mobile or not), also demand advanced approaches to harness them for marketing research and practice (Erevelles, Fukawa, & Swayne, 2016; Malthouse, Haenlein, Skiera, Wege, & Zhang, 2013). Analyzing all these data points creates both challenges and opportunities, revealing the continuing need to understand more about the specific contextual settings of mobile Internet usage (Ström, Vendel, & Bredican, 2014).

The Marketing Science Institute (2014) has reiterated the idea that leveraging mobile technology remains a research priority. With three independent essays, the present dissertation addresses these three outlined challenges and opportunities in the digital economy. The first study investigates how consumers contribute value to new business models, such as free e-services, without paying money. The second and third studies each deal with the role of a mobile channel (for online customer reviews or online auctions, respectively) and its interdependencies with non-mobile channels. Both studies involve big data sets, obtained from field observations, to achieve clear knowledge about the role of mobile devices.

1.2 Research Questions

The following sections motivate the research questions addressed in each study. The research scope and applied approach also are portrayed in more detail.

1.2.1 Study 1: Nonmonetary Customer Value Contributions in Free E-Services

The first project was designed to gain an initial understanding of managerial perceptions and decisions in the digital economy. In this joint project (Anderl, März, & Schumann, 2015), we focus on the vastly increased prevalence of business models that provide digital services and products to customers for free (Anderson, 2009; Bryce et al., 2011; Kumar, 2014). It is not a totally new, online-only phenomenon; free products and services often are used as marketing incentives or in promotional bundles (Bawa & Shoemaker, 2004; Kamins, Folkes, & Fedorikhin, 2009). Yet recent research increasingly deals with business models that are based fundamentally on non-paying customers, then asks how to monetize them, such as by transforming them into paying customers (Halbheer, Stahl, Koenigsberg, & Lehmann, 2014; Pauwels & Weiss, 2008). For online content providers, the trade-off between offering something for free and charging, with the risk of alienating their customer base, is existential (Lambrecht & Misra, 2015). Mobile app providers with so-called freemium versions also must manage the equilibrium between free, ad-based and ad-free, fee-based offerings (Appel et al., 2015).

Beyond the notion of moving from free to fee, the existing research rarely studies nonmonetary customer value contributions, such as resource contributions by customers beyond (future) monetary transactions. This research gap exists even though researchers have long recognized that direct revenues are not the only relevant source of customer value (Rust, Zahorik, & Keiningham, 1995; Zeithaml, 2000). Therefore, several research questions arise: *How do customers of free e-services contribute value without paying? What are the nature and dynamics of nonmonetary value contributions by nonpaying customers?*

To answer these questions, we conducted an interview study with 23 executive managers of a variety of free e-service providers, including some pure mobile players. The subsequent projects rely on the knowledge gained from this first study

to deepen our understanding of aspects of nonmonetary customer contributions from a mobile perspective.

1.2.2 Study 2: The Impact of Customer Attributions on the Perceived Helpfulness of Mobile- vs. Non-Mobile-Generated Customer Reviews

The first study revealed that the (quality of) co-production of original content is a crucial, nonmonetary customer value contribution, especially for user-generated content platforms. The fit with other customers also drives the network value of a customer by building or sustaining a homogeneous, interactive exchange. In this connection, the user's specific access channel might influence the methods for generating and perceiving content. One interviewee from Study 1, a manager of a question-and-answer platform (Interview P, Table 1), confirmed the changing character of co-produced content, due to the increasing participation of mobile users. The content of mobile-contributed questions or answers thus differs from that of non-mobile-generated items (e.g., fewer words or questions about time- and location-sensitive concerns such as alternate public transport connections).

Customer review platforms also depend on co-produced content and the fit between contributors and recipients; without relevant content, no reader would visit the platform, and without visitors, the platform could not monetize the attention devoted to the paying third party (e.g., advertising). Actually, the customer review platform deals with word of mouth (WOM), which is another, distinct, nonmonetary customer value contribution, at least for the reviewed product or company, as indicated by Study 1. Calls for research note the scarce knowledge available about the role of mobile devices as channels for content and WOM generation, and their interplay, for the perception of recipients (Berger, 2014; Hennig-Thurau et al., 2010). Thus, Study 2 asks, *Do recipients perceive mobile reviews as more authentic or helpful because they reflect the immediate consumption experience? Or do they dismiss them, because mobile reviews tend to be shorter and affect-laden?*

This project adds linguistic style-specific characteristics to examinations of review perception, which offer initial, notable insights into content-specific characteristics and their effect on perceived helpfulness (Lurie, Ransbotham, & Liu, 2014). To cope with the challenge of identifying the value of unstructured data, such as customer

reviews, new methods like linguistic analysis are required (Erevelles et al., 2016; Malthouse et al., 2013), as applied to the field data in Study 2.

Although including linguistic criteria provides a more fine-grained picture of the value of review elements, it cannot explain completely why mobile reviews are valued, unlike non-mobile reviews. There are good reasons to presume that source cues, such as the devices used in the present case (mobile or not), help determine fit with peers in the network. Perceived dissimilarity might cause non-mobile users to discount the value of mobile-generated reviews. Thus, a scenario-based experiment seeks answers to the following new questions derived from the field study: *Are there significant differences in helpfulness perceptions, reflecting the compatibility of the devices used by the recipient and the reviewer? If the mobile device used to create the review is incongruent with the non-mobile device used to read it, which mechanisms underlie appraisals of the review?*

1.2.3 Study 3: The Influence of Mobile Push Notifications on the Success Rate of Customers' Late Bidding

As revealed by Study 1, cross-market network effects are important to free e-services. A typical example is online auction platforms, whose nonpaying customers contribute value, taking into account cross-market network effects among buyers, who pay nothing to the platform, and sellers, who pay for brokerage services (Gupta & Mela, 2008). To foster these cross-market network effects, online (auction) platforms must draw the attention of their nonpaying customers to the offerings of their paying customers. Auction participants value their time significantly, so technological features are required to reduce their monitoring and bidding costs and increase the attractiveness of the platform (Bapna, Goes, Gupta, & Jin, 2004).

A prevalent strategy on online auction platforms is to wait to reveal one's own buying interest and bid only in the last minute (Roth & Ockenfels, 2002). Rational reasons support this strategy, as discussed briefly in Study 3. However, compared with a proxy-bidding agent, in which case customers submit their maximum willingness to pay, and the agent increases the bids automatically up to this maximum, a late bidding strategy invokes several drawbacks. First, users must exert effort to monitor the deadline on an interesting auction. Second, they risk missing the end of that auction, due to their potential unavailability (Kamins, Noy, Steinhart, &

Mazursky, 2011). The main focus of this joint research project (with Michael Lachner, Jan H. Schumann, Florian von Wangenheim, and Christian Heumann) is the promising role of push notifications as a mobile feature that can address these drawbacks.

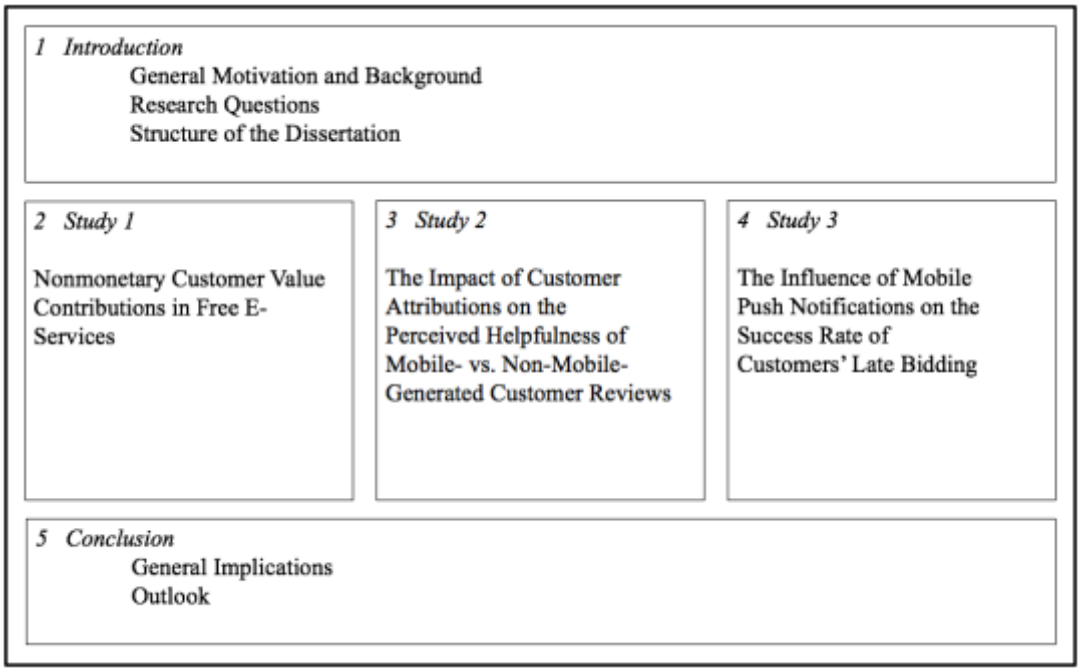
By using mobile notifications on the home screen of their mobile devices, as reminders of auction deadlines, prospective (late) bidders can participate in the respective auction anywhere and anytime. Mobile push notifications on these highly personal communication devices often are perceived as intrusive, but less so if users can co-produce the messages (Bacile et al., 2014). Therefore, as a complement to a late bidding strategy, users can customize their push notifications, which lessens the degree of perceived intrusiveness and gives the notifications a service-like character (e.g., as a reminder tool). As interactive features, mobile push notifications also might reduce the effort required and increase the bidding efficiency; late bidders with push notifications miss fewer deadlines, so they can increase their auction success rate. By analyzing transactional and behavior data at the individual level in an online auction platform, Study 3 addresses the following questions: *How do mobile push notifications affect (late) bidding behavior and particularly bidding success? How are mobile push notifications related to the winning chances of late bidders?*

1.3 Structure of the Dissertation

The dissertation proceeds as depicted in Figure 2. Following this introduction, the next chapter details the study of nonmonetary customer value contributions in free e-services. The study of mobile-generated customer reviews and perceptions makes up Chapter 3. Chapter 4 then summarizes the study on mobile push notifications and their effects on late bidding in online auctions. Finally, Chapter 5 synthesizes the central findings of all projects, including their implications for researchers and managers, and provides an outlook for further research.

Figure 1.

Structure of the Dissertation



2 Nonmonetary Customer Value Contributions in Free E-Services

Eva Anderl, Armin März, and Jan H. Schumann

Offering services for free, a prevalent business model online, raises new questions for both service providers and marketing researchers: How do customers of free e-services contribute value without paying? What are the nature and dynamics of nonmonetary value contributions by nonpaying customers? On the basis of a literature review and interviews with senior executives of free e-service providers, this article presents a comprehensive overview of nonmonetary value contributions in the free e-service sector, including word of mouth, co-production, and network effects, as well as attention and data as two new dimensions, which have not been addressed in prior marketing research. By putting these findings in the context of the existing literature on customer value and customer engagement, the authors shed light on the complex processes of value creation in the emerging e-service industry, while also advancing marketing and service research in general. This study identifies several promising research avenues, such as the question of the extent to which customers are aware of the nonmonetary value they provide firms.

Keywords: *customer value; CLV; e-services; free; nonpaying customers; nonmonetary value contributions*

2.1 Introduction

Offering services for free is increasingly prevalent—especially online (Anderson, 2009; Bryce et al., 2011). Consumers can choose from a multitude of free e-services, ranging from search and communication to entertainment and social networking. The overall market size of the "freeconomy" has been estimated at $260–$300 billion (Anderson, 2009). Research on how their customers contribute value without paying remains surprisingly scarce.

Despite ample research on free products and services as marketing incentives (Bawa & Shoemaker, 2004), trial versions (Jiang & Sarkar, 2009), or in bundles with other offerings (Kamins et al., 2009), researchers have only recently begun to address cases in which offering a service for free to at least a segment of the customer base is part of the main business model and not just a marketing tool. Several studies investigate moving from free to fee (Pauwels & Weiss, 2008) and the willingness to pay for free content (Halbheer et al., 2014; Papies, Eggers, & Wlömert, 2011). Finally, first research exists on competitive strategies in response to free or sponsor-based business models (Bryce et al., 2011; Casadesus-Masanell & Zhu, 2013).

However, scant research considers nonmonetary customer value contributions (NMCVCs), that is, resource contributions by customers that do not include a monetary transaction, in services that are completely free to end customers. While researchers have long recognized that direct revenues are not the only relevant source of customer value (Rust et al., 1995; Zeithaml, 2000), this study focuses on customers who contribute in a number of ways, but do not generate any direct revenues. As the concept of value is ambiguous and elusive (Grönroos & Voima, 2013), we restrict the term "customer value" to the value of a customer to the firm and do not reflect alternative usages taking a customer perspective (e.g., Payne, Storbacka, & Frow, 2008) or broader concepts of value co-creation in service-dominant logic (Vargo & Lusch, 2008).

For a provider of free e-services, the main NMCVCs that have been discussed to date—word of mouth (WOM), co-production, and network effects—seem to play an important role, yet they do not represent a customer's full value contribution and the resulting opportunities for monetization, that is the generation of monetary revenues. Many free e-service providers rely on monetizing attention by means of advertising and personal data, so it is surprising that these aspects have not been discussed in the customer value literature. It also is unclear whether and how the nature and dynamics of previously discussed NMCVCs might change in free e-services.

To fill this gap, we conducted an interview study with 23 executives of free e-service providers. We identify dimensions and roles of NMCVCs in free e-services and discuss the results against existing research on customer value and customer engagement. The contribution of our research is at least fivefold: first, we contribute

to research on free e-services by elaborating the nature and dynamics of NMCVCs. We confirm that WOM, co-production, and network effects are important NMCVCs for e-service providers, and identify attention and data as additional dimensions. We also extend existing knowledge on co-production and network effects by identifying three subtypes of co-production that are particularly relevant for free e-services and distinguishing three generic drivers of network effects. Second, we highlight attention and data as two NMCVCs that are core constituents of many free e-service business models but have been disregarded in customer value research. Third, we contribute to the customer engagement literature (Brodie, Hollebeek, Juric, & Ilic, 2011; Kumar, Aksoy, et al., 2010; van Doorn et al., 2010) by exploring the definitional boundaries of customer engagement behaviors (CEBs). Neither attention nor data comply fully with the existing definition of CEBs as voluntary behaviors resulting from motivational drivers. The lack of a clear distinction between motivational and nonmotivational behaviors for attention and data thus limits the discriminatory power of existing CEB definitions and provides opportunities for future research and theory refinement. Fourth, from a managerial perspective, conceptualizing NMCVCs and linking them to business outcomes helps managers reassess the value of nonmonetary customer contributions. We thus illustrate the limitations of revenue-based calculations of customer lifetime value (CLV). Finally, our findings can help managers of free e-services develop their customer concept. Understanding the different forms of nonmonetary value contributions is an essential first step for e-service providers to establish and manage customer relationships with their nonpaying customers.

2.2 Literature Review: NMCVCs

Since the first appeals to include WOM and other social effects when determining customer value (Rust et al., 1995; Zeithaml, 2000), a proliferation of studies has discussed NMCVCs. Most approaches for calculating CLV, which is one of the most widely used measures of customer value (Gupta et al., 2006), focus on transaction behavior and direct revenues from customers (Gupta et al., 2006; Venkatesan & Kumar, 2004). However, several researchers have proposed to extend the definition of CLV to cover selected NMCVCs, such as cost savings for customer acquisition (Lee, Lee, & Feick, 2006) or advertising ripple effects (Hogan, Lemon, & Libai,

2004). Recently, selected NMCVCs have gained increased attention in the customer engagement literature (Brodie et al., 2011; Jaakkola & Alexander, 2014; Kumar, Aksoy, et al., 2010; van Doorn et al., 2010): Kumar, Aksoy, et al. (2010) propose customer engagement value (CEV) as a concept that includes both CLV and value from other CEBs, namely customer referral value, customer influencer value, and customer knowledge value. Other researchers explicitly limit CEV to voluntary resource contributions that go beyond purchase transactions (Jaakkola & Alexander, 2014; van Doorn et al., 2010).

The main NMCVCs that have been discussed in prior research are WOM, co-production, and network effects. Prior research mostly covers NMCVCs as complements to monetary revenues. Studies on NMCVCs in free e-services are scant and predominantly focus on single NMCVCs.[1] Related research streams that do not explicitly examine the value of NMCVCs to the firm, such as research on the mechanisms of value co-creation in brand communities (Schau, Muñiz, & Arnould, 2009) or co-creation in new product development, represent valuable references for analyzing the dimensions of NMCVCs in free e-services in the following sections. For example, Sawhney, Verona, and Prandelli (2005) discuss how firms can use the distinctive capabilities of the Internet to access knowledge at low cost from individual customers and consumer communities.

2.3 Methodology

To gain a better understanding of the dimensions and roles of NMCVCs in free e-services, we conducted an interview study with industry experts. Our qualitative sample consists of 23 executives of German free e-service providers with different business models (e.g., ad-financed communities as well as ad-free browser games with premium access) and in different company stages (e.g., established publishing houses as well as start-ups). Following Strauss and Corbin (1990), we stopped our sampling procedure at the point of saturation. The number of interviews we conducted is consistent with sample sizes recommended for exploratory research (Guest, Bunce, & Johnson, 2006). We conducted interviews between January 2012

[1] An overview of the existing literature on NMCVCs including the dimensions in focus, the research approach, the industry context, and key findings can be found in the Appendix 1.

and February 2013, which lasted between 40 and 75 minutes. Table 1 provides an overview of the interviewees.

In the beginning of the interviews, respondents described the business model and key stakeholders of their firms. Subsequently, we focused on the value of nonpaying customers to the firm. Respondents indicated different dimensions of NMCVCs and their business outcomes. To elicit the nature and dynamics of NMCVCs, we followed up with open questions such as "What are opportunities and challenges related to this dimension?" Interviews concluded with respondents describing their company and specific roles.

Each interview was recorded and transcribed verbatim. Our analysis followed a thematic analysis approach (Boyatzis, 1998; Braun & Clarke, 2006), in which two researchers independently open-coded the transcripts to identify relevant themes. After comparing and discussing the results and matching them with the existing literature, we jointly developed a coding plan that included five major types of NMCVCs, subtypes for each NMCVC, outcomes, and managerial challenges. The final coding scheme consisted of 39 codes with 1,996 quotations.

We assessed the intercoder reliability between the two judges for the final codings with two measures. The proportional agreement of .86 exceeds the recommended threshold of .80 (Neuendorf, 2002). The value of the Perreault and Leigh (1989) measure is .92, well above the .90 cut-off point for advanced marketing research (Rust & Cooil, 1994). Therefore, we are confident that our results are valid and reliable.

Table 1.

List of Interview Participants (Study 1)

Interview	Function	Business field	Number of employees	Founded in
A	CRM Manager	Online gaming provider	>200	2005
B	General Manager	Publishing house	>200	1949
C	General Manager	Online community	10–49	2011
D	General Manager (Digital)	Publishing house	50–199	2001
E	General Manager	Online career network	10–49	2000
F	General Manager	Online community	10–49	2010
G	General Manager	Online community/ application provider	10–49	2011
H	Marketing Manager	Real estate marketplace	>200	1997
I	General Manager	Online community	<10	2009
J	General Manager	Online news portal	<10	2010
K	General Manager	Software provider	50–199	2003
L	Head of Operations	Online community	10–49	2002
M	General Manager	Online community	10–49	2012
N	Marketing Manager	Couponing app	10–49	2009
O	General Manager	Tariff consultancy	<10	2012
P	Marketing Manager	Online community	50–199	2006
Q	General Manager (Digital)	Publishing house	>200	1946
R	Marketing Manager	Price comparison website	>200	1999
S	Marketing Manager	Online route planner	10–49	2010
T	General Manager	Price comparison website	>200	1999
U	Head of Strategy	Online marketplace	>200	1993
V	General Manager	Price comparison website	50–199	1999
W	General Manager	Publishing house	>200	1974

Note. For interview quotes, the alphabetic label identifies the interviewee, and the numeric label refers to the line of the respective transcript.

2.4 NMCVCs in the Free E-Service Industry

2.4.1 Word of Mouth

Our interviews confirm the importance of WOM—the most frequently mentioned NMCVC in the existing literature—for free e-services. We use a broad definition of WOM, including interpersonal, oral, and product- and service-related communication (Westbrook, 1987); digital, anonymous, and widespread electronic WOM ([eWOM]; Hennig-Thurau & Walsh, 2003); and incentivized referrals (Kumar, Petersen, & Leone, 2010). In line with the existing research, we can distinguish *referral* value and *influence* value using motivation as the differentiating factor (Kumar, Aksoy, et al., 2010). Referrals are extrinsically motivated, incentivized recommendations. Free e-service providers actively foster the acquisition of nonpaying customers through WOM with referral programs or software tools that facilitate recommendations in online networks. Managers even give monetary rewards to free customers for recruiting other free customers (A72, F37, and S64). Intrinsically motivated WOM is a highly valued marketing instrument in free e-services; often referred to as "viral marketing". The intrinsically motivated influence of a nonpaying customer can consist of a broad range of personal or anonymous, vocal or digital, well-argued or simple "like"-based forms of WOM messages.

Direct monetization of WOM by free e-service providers seems rare. A majority of respondents emphasized that the business value of WOM in free e-services lies in cost savings for customer acquisition, such as: "We just spend a lot of money to generate traffic on our website […]. When a user takes over this job, we immediately save money. And that's the value" (D82). While measuring WOM referrals on an individual level is relatively easy, influence is mainly seen as a "black box" (L121). Accordingly, managers of free e-services identify measurability as the most important managerial challenge related to WOM as an NMCVC. This gap reflects prior research on CEB, where the value of intrinsically motivated influence by customers, conceptualized as customer influencer value, has not been analyzed in full detail yet (Kumar, Aksoy, et al., 2010). New methods, such as linguistic analysis, are required to identify the value of unstructured eWOM and relate it to individual customers (Bijmolt et al., 2010).

2.4.2 Co-Production

Co-production is defined as customer participation in the creation of the core offering itself through shared inventiveness, co-design, or shared production (Lusch & Vargo, 2006). Whereas previously discussed aspects of co-production include learning from customers (Ryals, 2002) and customer knowledge (Kumar, Aksoy, et al., 2010), as well as customer participation in new product development (Hoyer, Chandy, Dorotic, Krafft, & Singh, 2010; Sawhney et al., 2005), we find three subtypes of co-production that are especially important in the free e-service sector: first, the *co-production of content* (user-generated content [UGC]) comprises the co-production of original content (e.g., texts, photos, and videos) and the enrichment of the existing content (e.g., tagging and translation). In particular, managers of free e-services with a business model based on UGC strongly rely on customers' willingness to co-produce. Content enrichment by customers can either advance the original contributions of other customers or help improve the services provided by the company itself. For example, nonpaying customers participate in translating a browser game and online manuals into other languages (A78). Second, customer knowledge is confirmed as an important value contribution, particularly in the form of constructive feedback to the company. We amplify this concept as *co-management*, because customers of free e-services not only provide knowledge but also apply their knowledge in customer-to-customer support in forums or take over quality management: "Our users do the quality check. They usually spot fake reviews from agencies or competitors rather quickly" (R54). Co-management thus extends the concept of customer knowledge value (Kumar, Aksoy, et al., 2010). Third, an important aspect of co-production in the free e-service sector is *brand co-creation* (Hatch & Schultz, 2010). As one manager noted, "Our brand lives from the people using our service" (G74). Customers co-create brand value and sometimes even participate in marketing communications, all for free. Similarly, prior research has asserted that brands belong to and are created in concert with communities (Brown, Kozinets, & Sherry, 2003).

Direct monetization of co-production, however, is rare; although there are some exceptions: an online photo community is successfully experimenting with licensing customers' co-produced content for a commission fee (G132). Given this limited

direct monetization, most respondents define the business value of co-production in terms of cost savings for content production or support.

Motivation is an important challenge for free e-service providers relying on co-production. Managers need to "push the right buttons" (F98) to trigger co-production. The drivers mentioned by the interviewees are consistent with the existing literature on motivations for producing eWOM (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004) or providing support in firm-hosted communities (Dholakia, Blazevic, Wiertz, & Algesheimer, 2009): Desire for social interaction, concern for others, and the potential to enhance their own self-worth all can spur customer co-production. Monetary incentives also play a role, but managers use them sparingly, noting that "We made a conscious choice not to provide monetary incentives, because that would attract people who just come for the money" (P210). Companies instead try to increase the approval utility customers can derive from participation by implementing rewards systems and evaluation features. Respondents repeatedly raised quality concerns about co-produced content. Since value is created primarily between and among customers in many free e-services (Kuppelwieser, Simpson, & Chiummo, 2013), managers must ensure the quality of customer co-production, which can require very complex, costly quality management processes. Sustaining co-production quality without demotivating customers remains a challenge for e-services managers and further research.

2.4.3 Network Effects

Both *intra-* and *cross-market network effects* play an important role in free e-services. Intra-market network effects arise if the value of a service is an increasing function of the network's size (Katz & Shapiro, 1985). Cross-market network effects occur in multisided markets when a firm offers different products or services in two or more markets and the value of one product or service depends on demand for the other (Stremersch, Tellis, Franses, & Binken, 2007). By linking paying and nonpaying customers, cross-market network effects often provide a basis for monetization. Although network externalities have been covered extensively in the economics literature (see Stremersch et al., 2007), their inclusion in customer value or customer equity calculations is more recent. Gupta and Mela (2008) analyze the value of a nonpaying customer for an auction platform, taking into account cross-

market network effects among buyers, who do pay nothing to the platform, and sellers, who pay for brokerage services. Due to network effects, nonpaying customers can be valuable resources for a free e-service provider: "This is comparable to the purchasing department of other companies. We pay for the acquisition and retention of nonpaying customers who we finally try to place in the job market" (E18).

Intra-market network effects also drive the attractiveness of free e-services for other customers. Interactive games or interaction-based communities depend on active users who keep the user experience interesting: "Nonpaying customers are extremely important to keep the game alive… In the end, many games rely on constantly getting new players" (A38). The manager of an online community highlighted the value of interconnectedness in- and outside the focal community for customer acquisition: "We prefer digital natives, who are blogging, networking on Twitter and Facebook, and sharing interesting offerings and comments on our platform with many followers" (I38). Our findings are congruent with the existing research on (online) social networks: intra-market network effects influence both activity levels (Trusov, Bodapati, & Bucklin, 2010) and customer retention (Nitzan & Libai, 2011).

Most of the managers emphasized the value of the sheer number of nonpaying customers for attracting additional nonpaying and paying customers: "The mere fact of their existence and their existence in a significant number constitutes a value" (N104). This effect is enhanced in multisided markets, which are particularly prone to winner-take-all dynamics (Eisenmann, Parker, & van Alstyne, 2006): "If you are the dominant platform, you can just name your price. In fact, you could stop your marketing activities because sellers must use your platform anyway" (U53). In addition to quantity, we identify three qualitative drivers that determine a customer's contribution through network effects. The network value of customers can be specified and amplified by (1) their *fit* with other customers, (2) their *reputation*, and (3) their degree of *interconnectedness* both within and outside the platform or community. These drivers work for both cross-market and intra-market effects, but to varying extents. The fit and reputation of free customers ensures a compatible and attractive target group for third parties, such as advertisers or employers in a career network. The more detailed a free e-service provider can describe its target group, the more interesting that free customers become for third parties willing to pay for

customer acquisition. Fit and interconnectedness also are important drivers of intra-market effects for building or sustaining a homogeneous, interactive exchange (e.g., on social network sites or browser games). Several managers reported that deviant user behaviors by new customers of different cultures or age groups confused and discouraged existing customers (C75, G124). Fit, also known as assortativity, and interconnectedness have been confirmed as drivers of network effects in specific contexts (Katona, Zubcsek, & Sarvary, 2011; Nitzan & Libai, 2011); we posit that they actually apply more broadly to most of the free e-services in our sample.

2.4.4 Attention

The majority of respondents emphasized the importance of attention as a NMCVC in free e-services: "Our customers pay with attention" (K8). Nevertheless, attention has not yet been conceptualized as a customer value contribution in the prior (service) marketing literature. In line with the advertising research (Vakratsas & Ambler, 1999), we conceptually differentiate attention as *exposure* and *behavioral response*. Exposure is a passive construct, which managers often described as aggregate reach or visibility. For one manager, the mere existence of a customer indicated potential attention: "And hopefully, this existence then turns into attention" (D126). In contrast, behavioral responses are active customer reactions following attention, such as clicks on links and offers, particularly on advertisements or affiliate offers, and successful transactions with third parties.

Attention is often the only customer value contribution that free e-services monetize. Potentially the most widespread revenue model based on customer attention is advertising, which is a major revenue source for media and many free e-service providers (Anderson, 2009). Whereas advertising is paid mass-communication, which can include both simple exposure and behavioral responses, successful brokerage always requires a behavioral response from the nonpaying customer. Brokers act as platforms to enable actual transactions between two parties and, as such, strongly rely on cross-market network effects. Free e-service examples include real-estate brokerage platforms, job markets, and other marketplaces.

Monetization of customer attention through third parties is strongly reliant on cross-market network effects. Thus, the previously identified drivers of network effects

also determine monetization success. Successful monetization is contingent on crossing a quantitative threshold, in that "You can only start to think about monetization once you have reached a certain threshold" (J88). Managers of free e-services also need to provide clear target groups with high fit that are attractive to third parties. For example, compared with a news platform that has a broad, anonymous user group, the provider of a secondhand fashion community can charge a significant price premium for the attention of the service's specific target group (i.e., young, female fashion consumers; I46).

Many of the managers we interviewed view the balance between monetizing attention and other NMCVCs as risky: "On the one hand, we have to increase the value of attention to beef up our business model; on the other hand, we must not be too pushy and scare off our users" (C75). Although some interviewees had a positive outlook—"I believe that everybody knows that you need to refinance free services. Therefore, advertising is well and sustainably accepted" (Q80)—most managers believe that they need to compromise to make a living (R72): "Advertising is increasingly perceived as annoying. Accordingly, some people feel like they are being used to create value. But not in a positive way" (B126). According to one interviewee, attention and other NMCVCs are in a love–hate relationship (P116): "As soon as you reduce advertising, some KPIs [time spent on site, clicks, number of referrals] will automatically improve. If you increase advertising, these KPIs will deteriorate. So, there's always a conflict of interest" (P116). Two platforms in our sample that strongly rely on UGC explicitly decided not to bother content contributors with advertising. They clearly differentiate between their co-producing customer base and readers whose attention is offered to third parties (R10, P116).

Along with directly monetizing attention, many of the free e-service providers we interviewed take advantage of their customers' attention to upsell paid offerings or cross-sell additional services. In the freemium model, basic service is available to consumers for free, whereas premium services are only accessible for a fee (Kumar, 2014). The free offer in freemium models is usually not limited in time and coexists simultaneously with chargeable premium versions, such that gaining customers' attention for up-selling options is crucial for business success: "Attention helps us create new revenue streams" (A124). Cross-selling offerings in free e-services often are again free; that is, there are no transaction fees between the website operator and

customer. For example, the manager of a comparison website for energy providers confirmed high cross-selling rates of customers who look for a new gas provider and later change their energy supplier using the same service (T24).

2.4.5 Data

Most of our interview partners identify data as an important NMCVC in free e-services: "The most important value contribution? In our case, that's obviously data" (G88). Related research streams on direct marketing or business intelligence point out the decisive role of data, such as for personalization and targeting (Chen, Chiang, & Storey, 2012). However, an explicit integration of data in CLV conceptualization or calculations is missing. To our knowledge, data have not been conceptualized explicitly as customer value contributions in the (service) marketing literature.

In addition to volunteered *profile data*, the e-service industry can gather a myriad of *behavioral data*, such as clicks and browsing patterns: "Data are extremely important for us to see how users move inside the platform. Which user uses which elements, posts activities, etc.?" (M34). There is a market value for certain types of customer data, especially address data, so that data can be translated into revenues via data intermediaries (Pancras & Sudhir, 2007). Prior research has shown how to use data to grow CLV by increasing marketing effectiveness and cross-selling through personalized recommendations (Bodapati, 2008), but this use covers only a small part of the full value contribution to free e-service providers.

In particular, specialized social networks like outdoor communities rely on data and the enrichment of data points as core resources: "Our value consists of a database of destinations, which is as comprehensive as possible. We connect to different [external] data sources, but our database will never be complete. Therefore, we have to permanently incentivize our members to supply destinations, photos, etc." (M82). Similarly, GPS data points generated by customers that are used to improve routing algorithms constitute an important asset for an outdoor community (S16). In addition, data represent an important enabler for harnessing the monetary value of attention. Better ad targeting and personalized, individualized offerings can enhance ad effectiveness (Iyer, Soberman, & Villas-Boas, 2005). In turn, free online platforms become more attractive for advertisers and can increase revenues if they

offer data-driven targeted advertising (Schumann, von Wangenheim, & Groene, 2014). As one manager emphasized, "without exact profile data, our advertising wouldn't be better than in any other network" (F59). Free e-service providers can also use data provided by nonpaying customers for analytics and market research—internally or for third parties. For example, a real-estate marketplace in our sample consolidates data from all listings to calculate a property value index, which users can access for a small fee (U22).

Using data provided by customers as a resource raises some specific managerial challenges though. Many e-service providers seemed reluctant to directly monetize data provided by customers, because they fear negative reactions: "If you [sell customer data], you take a huge risk; in the worst case, you could destroy your whole business" (K48). But when using data as an enabler, managers of free e-services still must address the trade-off between customers' privacy concerns and their own and third parties' need for data richness. Our interviews suggested that aligning the value creation processes can reduce privacy concerns: "Nobody has ever said, you just want my data to sell it—our value-in-use is just too high for that" (M87). Future research therefore needs to integrate the customer perspective: When are consumers aware that providing data constitutes a valuable contribution? Do value perceptions depend on how the data are used or the types of data? What effects does awareness or its lack have for free e-service providers?

2.5 Discussion

Building on a literature review and an interview study with managers of free e-services, this study provides a comprehensive overview of NMCVCs in the free e-service industry. Our findings contribute to the free e-service and value literature, related research fields such as customer engagement, and managerial practice in multiple ways. First, we contribute to research on the emerging free e-service sector (Anderson, 2009; Bryce et al., 2011; Casadesus-Masanell & Zhu, 2013) by carving out the dimensions and roles of NMCVCs in free e-services. In addition to confirming WOM, co-production, and network effects as important NMCVCs and identifying attention and data as additional dimensions, we extend the existing knowledge on co-production and network effects. Whereas the value and characteristics of WOM seem comparable for paying and nonpaying customers, we

identify three subtypes of co-production that are especially important in free e-services: co-production of content, co-management, and brand co-creation. In addition, our interview study approach, which covers a broad range of business models, enables us to distinguish three generic drivers of network effects. The network value of customers of free e-services is determined by their fit to other customers, their reputation, and their degree of interconnectedness. Although fit and interconnectedness in particular have been identified in prior research (Katona et al., 2011; Nitzan & Libai, 2011; Vock, van Dolen, & de Ruyter, 2013), we are the first to apply them consistently for intra-market and cross-market network effects.

Second, we highlight two dimensions of NMCVCs, attention and data that have not been discussed in research on customer value. Both dimensions are core constituents of many free e-service business models, but they also serve a role outside this domain. For example, media firms such as television channels or newspapers can be financed by advertising revenue, by direct payment from the viewers, or both in combination (Kind, Nilssen, & Sørgard, 2009). Using attention to encourage cross- and upselling seems very common. Similarly, the value of data provided by customers is not limited to e-services, though the Internet facilitates data collection. Our findings thus advance knowledge on the value of nonpaying customers in e-services and contribute to research on customer value in general.

Third, the identification of attention and data as NMCVC dimensions contributes to customer engagement research by exploring the definitional boundaries of CEBs. Although the overall scope of CEBs remains under discussion, a broad consensus suggests that CEBs are "behavioral manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers" (van Doorn et al., 2010, p. 254). Both attention and data do not always seem to comply with the existing definition of CEBs in that paying attention or providing data are not always motivated or even conscious acts: on the one hand, for many free e-services, use without providing attention and data is impossible. Prior research shows that even incidental and involuntary exposure to advertising can change consumer attitudes (Janiszewski, 1993) and therefore is of value to free e-service providers. According to the existing definition, incidentally providing value in the form of attention would not qualify as CEB. Instead, it would rather require motivational drivers to avoid contributing attention or data by using tracking protection or ad-blocking software.

On the other hand, some customers actively argue in favor of advertising, referring to reciprocity arguments and—supporting the existence of motivational drivers: "Sometimes there are discussions on annoying ads, for example, layer formats […]. Many users then start fretting, but others try to calm them down; the platform is for free, and somehow they just have to make money" (I68). Similarly, data provision, especially profile data, is often voluntary and reciprocity appeals can increase willingness to provide personal information for targeted advertising (Schumann et al., 2014). The fact that, according to the existing definition, the same NMCVC, such as watching an advertisement, can qualify as CEB or not—depending on the customer's psychological state, provides several opportunities for future research and theory refinement: What are the definitional boundaries between motivational and nonmotivational behaviors towards the firm? Does choosing not to use options to reduce NMCVCs, like not skipping an ad, qualify as CEB? What are the implications for free e-service providers if data or attention are provided voluntarily? How does creating awareness for previously nonmotivational NMCVCs influence other CEBs?

Fourth, linking NMCVCs to business outcomes for the firm can help managers reassess the value of the nonmonetary contributions that customers provide. Even though there are existing market prices for certain types of attention or data, for example CPM or the value of address data for data intermediaries (Pancras & Sudhir, 2007), our analysis outlines the shortcomings of using market prices as a proxy for a customers' full value contributions. This approach could not acknowledge that customer segments are of differential value to advertisers depending on consumer-specific characteristics such as their socio-demographics or interests (Wilbur, 2008). Despite the fact that the advertising market is shifting its focus from mass marketing to targeted advertising and single consumers (Iyer et al., 2005), we know of no research into the value of the attention of an individual customer.

In this sense, we also demonstrate the limited applicability of a revenue-based definition of CLV for free e-service providers. Without accounting for NMCVCs, these companies would have no feasible instrument to measure the customer equity of large parts of their customers. Our approach is more comprehensive than including just cost savings for customer acquisition (Lee et al., 2006), in that it considers other customer relationship stages (e.g., retention), co-creation or co-management of the core offering, and monetization potential. Insofar, we extend the discussion on CEV

(Jaakkola & Alexander, 2014; Kumar, Aksoy, et al., 2010; van Doorn et al., 2010). Fifth, our findings grant managers to gain a more nuanced view of NMCVCs, enabling them to develop their customer concept. Many of the managers we interviewed initially did not view their often anonymous and nonpaying users as customers, "because customers always pay" (B22). Comprehending NMCVCs is an essential first step for e-service providers to establish and manage customer relationships with their nonpaying customers: "Our biggest opportunity is to build real customer relationships" (B152).

2.6 Outlook

Several limitations of our study provide fruitful avenues for further research. First, our work is conceptual and qualitative in nature. Further quantitative empirical validation could reconfirm our findings on a larger scale and create a link between managerial perceptions of NMCVCs and performance measures for the business success of free e-service providers. Our research also yielded some indications that the valuation of NMCVCs varies along different business models and company stages. Start-ups seem to rely on NMCVCs that foster their growth and reach, whereas later-stage companies focus on monetization by third parties. Regarding business models, it seems to make a difference whether a given NMCVC is part of a firm's core offering or mostly necessary for more efficient monetization. In general, nonpaying customers who contribute to the firm's core offering, such as by co-producing content, were more highly valued than customers providing attention. It would be worthwhile to determine whether these differences can serve as a basis for developing a typology of free e-services that can be confirmed by empirical results.

Second, our study represents the managerial perspective on NMCVCs in free e-services. Further research should examine whether and to what extent customers are actually aware of contributing value to free e-services and how it affects their willingness to contribute, as well as their actual contribution behavior. Understanding the customer perspective will help achieve a better alignment of value creation processes and thereby contribute to the development of sustainable free e-service business models based on NMCVCs. Investigating to what extent NMCVCs, such as attention and data, result from motivational drivers also can provide

important insights for reconciling these dimensions with the existing definitions of CEBs.

Third, our research only touches on the question of how to measure NMCVCs. Measurement emerged as an important challenge in our interviews. All firms in our sample monitored online customer behavior using tracking and analytics tools, but none of them measured nonmonetary customer value on an individual "micro level" (N86). Additional studies need to find ways to identify individual-level customer contributions, then measure and integrate them in customer value and customer equity calculations. Such metrics would be relevant for free e-services and also help managers of other firms to better understand the value of their customers.

Finally, we focused on the free e-service industry, which constitutes an interesting research object by itself. However, as an extreme case without any monetary revenues from end customers, this industry also might be regarded as a magnifying glass that highlights important new aspects of NMCVCs in general. Further research should investigate the applicability of our findings—especially regarding the newly identified dimensions of attention and data—in a broader context, using the free e-service industry as a starting point.

3 The Impact of Customer Attributions on the Perceived Helpfulness of Mobile- vs. Non-Mobile-Generated Customer Reviews

Armin März

The proliferation of mobile devices means that mobile-generated electronic word of mouth is on the rise too, though research into its peculiarities and appraisal is rare. With field data and a scenario experiment, the author demonstrates that recipients perceive mobile-generated customer reviews fundamentally differently from other reviews: first, they discount the helpfulness of mobile reviews, due to their text-specific particularities in content and style. Second, the simple fact that a review has been identified as written on a mobile device lowers recipients' perceptions of its value. Recipients use information about the device as a source cue to assess their compatibility. If they perceive themselves as compatible with the device, recipients perceive the review as more helpful, because they attribute the review to the quality of the reviewed subject; if they regard it as incompatible, recipients assume the review reflects the personal dispositions of the reviewer and discount its helpfulness. Managers of online opinion platforms thus must acknowledge the peculiarities of mobile-generated reviews and the impact of tagging content as mobile or not.

Keywords: *attribution; compatibility; customer reviews; mobile devices; perceived helpfulness; source cue*

3.1 Introduction

On pace with the widespread adoption of mobile devices (Nielsen, 2013), mobile-created electronic word-of-mouth (eWOM) is on the rise—eWOM is "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, p. 39). Customers employing their mobile devices anytime and anywhere (Balasubramanian et al., 2002; Okazaki & Mendez,

2013) share their experiences with other potential customers, such as during or immediately after a consumption experience, using text, images, or voice messages (Hennig-Thurau et al., 2010). Firms encourage such practices, asking customers to rate and review their experiences mobile. Yet despite its span and potential influence, little evidence specifies the precise effects of mobile-created eWOM on other consumers. Do recipients perceive mobile reviews as more authentic or helpful because they reflect the immediate consumption experience? Or do they dismiss them, because mobile reviews tend to be shorter and affect-laden?

Prior research on eWOM in general does not answer these questions; it mainly addresses how and why eWOM affects recipients, without elaborating on potential differences across eWOM channels (Berger, 2014; King, Racherla, & Bush, 2014). Evidence related to uses of mobile devices primarily involves the motives that drive senders to undertake word-of-mouth behavior (Okazaki, 2008, 2009; Palka, Pousttchi, & Wiedemann, 2009). Lurie et al. (2014) offer some notable insights, with their consideration of mobile reviews as a standardized variety of eWOM that features text and ratings. They find that mobile reviews differ from non-mobile reviews in terms of their content-specific characteristics, some of which increase perceived helpfulness, while others decrease it. These authors also show that mobile reviews exert negative effects on recipients' value perceptions, simply because they are mobile. However, Lurie et al. (2014) do not elaborate on how and why mobile reviews might affect recipients' appraisals.

The current study extends research on customer perceptions of mobile reviews by using both a field study (Study I) and a scenario-based experiment (Study II). Study I leverages findings that style-specific aspects of review texts can explain the perceived helpfulness of eWOM (Ludwig et al., 2013; Schindler & Bickart, 2012). The findings of this field study confirm that including style criteria in analyses of online reviews yields a better understanding of the perceived helpfulness of mobile reviews, because the style-specific characteristics differ significantly across review channels and influence the perceived helpfulness of a review. However, the negative effect of mobile reviews persists beyond the contribution of these style-specific characteristics. Therefore, Study II adopts a scenario-based, online approach to hold the content and style of one review constant over various experimental conditions that manipulate only the information about the device used to write the review.

Identifying the same review as written on either a mobile or non-mobile device leads to significant differences in helpfulness perceptions, reflecting the compatibility or incompatibility of the devices used by the recipient and the reviewer. If the device used to create the review is congruent with the device used to read it, recipients sense compatibility and perceive the review as helpful, because they attribute the motivation for the review to the reviewed product or service. However, perceptions of incompatibility lead recipients to assume the review reflects only the personal dispositions of the reviewer, such that it appears less helpful. Therefore, empirical evidence affirms that the device to create a review has an indirect effect on helpfulness perceptions, through compatibility considerations and attributions by the recipient.

These finding contribute to relevant theory. First, this study extends the existing research on mobile-created eWOM (Lurie et al., 2014; Okazaki, 2008, 2009; Palka et al., 2009) by extending and validating the available evidence that the peculiarities of mobile devices (e.g., real-time creation) affect how users write customer reviews, such that they are distinct from customer reviews written on non-mobile devices. These characteristics influence the perceived helpfulness of mobile reviews. But simply citing a review as mobile (or not) also influences judgments of helpfulness, depending on whether the device used to create the review aligns with the device used to read it. The study thereby answers calls for research on the effects of mobile-created content on other customers (Berger, 2014; Hennig-Thurau et al., 2010; Shankar & Balasubramanian, 2009).

Second, this study extends research on the role of source cues in online customer reviews (Forman, Ghose, & Wiesenfeld, 2008; Naylor, Lamberton, & Norton, 2011; Racherla, Mandviwalla, & Connolly, 2012) by identifying the device used to write a review as a viable cue. Recipients use this cue to compare themselves to the reviewer and determine if the review will be helpful, in line with theory related to shared social identities (Forman et al., 2008; Naylor et al., 2011). By showing that perceived compatibility leads to helpfulness perceptions, because readers attribute the motive for review creation to the reviewed item, not to personal dispositions, the present study also explains how a shared social identity can improve evaluations of reviews, an issue overlooked previously in research on source cues.

Third, the present study helps explicate how compatibility affects technology and innovation usage intentions (Kleijnen, de Ruyter, & Wetzels, 2007; Meuter, Bitner, Ostrom, & Brown, 2005; Moore & Benbasat, 1991). The compatibility of a recipient's device with the device used to create a review strongly influences evaluations of the helpfulness of a review. Combined with prior findings that indicate that compatibility considerations are important when people choose whether to use a new technology, these findings extend prior evidence to reveal that compatibility considerations emerge in social communication situations in which communication partners use certain technologies. The perceived compatibility in technologies used informs people's judgments of the credibility of the content.

Fourth, as a contribution to review helpfulness research, this study introduces function words and verbal immediacy as two important style characteristics. Most prior research focuses on content criteria (e.g., number of words, affective content, rating; Lurie et al., 2014; Scholz & Dorner, 2013) or normative style (e.g., positive versus negative style elements; Schindler & Bickart, 2012). The present study also shows that function words and verbal immediacy influence review helpfulness, by providing recipients with additional information about the reviewer and the review, not conveyed by the content. This additional information helps recipients judge the value of any given review.

The findings also may prove valuable for managers. Online opinion platforms need to recognize that mobile reviews appear less helpful, due to their style and content peculiarities. These results challenge the current practice of tagging content according to the device used to create it, because this tag can induce a "boomerang effect" if recipients sense incompatibility.

After a brief overview of prior research on mobile reviews in the next section, this article continues with the field study (Study I) and its results. The findings of Study I provide a foundation for the conceptual framework for Study II, tested in a scenario-based experiment. Finally, the authors discuss the results and their implications for research and practice.

3.2 Study I: The Different Styles and Content of Mobile Versus Non-Mobile Reviews

3.2.1 Theoretical Background

Channel characteristics shape what and how people talk and discuss in their word of mouth (Berger & Iyengar, 2013), though the mobile-specific characteristics remain relatively unknown. To investigate whether mobile versus non-mobile customer reviews differ in their creation or perceptions, Lurie et al. (2014) argue that the particularities of the creation process for mobile reviews—namely, the possibility of real-time engagement, the high physical and cognitive costs of creation due to the small screen and keyboard sizes, and the strong personal ties to the mobile device—influence the way mobile reviewers write and rate the reviewed topic. Their evidence that mobile and non-mobile reviews differ, according to field data from a restaurant review platform, specifies that mobile reviews are shorter, are less extreme but rather negative in their ratings, contain more affective and less cognitive cues, and use one-sided negative or positive language. They also report more on current concerns (e.g., work, money), and less on social aspects (e.g., references to other people). Many of those content-specific characteristics influence how recipients perceive reviews. For example, recipients perceive reviews with fewer words, less extreme ratings, and fewer social aspects as less helpful, though other content-specific aspects do not exhibit a significant effect. In another intriguing finding, Lurie et al. (2014) note that mobile reviews—identified by a corresponding symbol—earn less helpful ratings, even after controlling for content-specific characteristics and rating- or reviewer-specific aspects. In this work, Lurie et al. (2014) focus on content words, which are valuable for assessing the basic information contained within a textual element. However, they do not determine the style of a text-based communication, that is, how senders convey information to recipients (Ireland & Pennebaker, 2010). Yet Ludwig et al. (2013) note that writing style is crucial in determining the appraisal of customer reviews.

Study I therefore extends the research framework proposed by Lurie et al. (2014) by introducing function words and verbal immediacy as two central style elements of customer reviews. The research goal is to explain why mobile reviews are still perceived as less helpful, even after controlling for content-specific elements.

Linguistic style is very context specific (Niederhoffer & Pennebaker, 2002), so both style elements should vary significantly between mobile and non-mobile customer reviews, as well as being linked to the helpfulness of customer reviews.

3.2.2 Hypotheses Development

Function words help readers evaluate customer reviews (Ludwig et al., 2013). Function words are pronouns, prepositions, articles, conjunctions, or auxiliary verbs that reveal the relationships of the sender to the topic of communication and among content constituents (Tausczik & Pennebaker, 2010). For example, senders use pronouns (e.g., "I," "it," "here") to refer to other persons, objects, places, or time. Prepositions often serve to provide more and more concrete information about a topic (Chung & Pennebaker, 2007; Tausczik & Pennebaker, 2010). The physical and cognitive costs of writing texts on mobile devices likely leads to the use of varying numbers of function words in mobile versus non-mobile reviews. Consumers have learned to write short messages on mobile phones, relying on character restrictions such as abbreviations and acronyms (Grinter & Eldridge, 2003; Ling & Baron, 2007), so their word usage is limited and closely considered (Lurie et al., 2014). Furthermore, mobile devices are convenient for quick, immediate responses, rather than for elaborated responses. Therefore, mobile reviews likely are characterized by fewer function words, because recipients consider them relatively unnecessary compared with key content.

H1: Mobile customer reviews include fewer function words than non-mobile customer reviews.

The use of function words in one review also might fit with the use of function words in other reviews of the same category to varying degrees. Ludwig et al. (2013) show that when a review shares more function words with other reviews in that category, its persuasion increases. However, no evidence indicates whether customer reviews containing function words perform better per se. By revealing the links between the reviewer and the subject, as well as among content elements, function words should give recipients a more fine-grained picture of the situation being reviewed. That is, function words enrich the informational content of a review by contextualizing the content elements, even when full understanding requires shared social knowledge

between the communication partners (Chung & Pennebaker, 2007). Hartley, Pennebaker, and Fox (2003) reveal that using more pronouns and prepositions facilitates manuscript readability, by conveying complex relationships in an understandable way. Research on customer reviews also notes that increased informational content coincides with an increase in the helpfulness of a review (Mudambi & Schuff, 2010; Weiss, Lurie, & MacInnis, 2008). Therefore, customer reviews that contain more function words should be more helpful to recipients than customer reviews with fewer function words.

H2: The number of function words has a positive effect on consumers' perceptions of the helpfulness of customer reviews.

Verbal immediacy offers another stylistic factor that likely differs between mobile and non-mobile reviews, due to the real-time nature of mobile communication. This linguistic style is characterized by the use of "concrete, personal, involved, experiential language with a focus on the here and now" (Borelli, Sbarra, Mehl, & David, 2011, p. 342). Verbal immediate language uses first-person singular, present tense, and discrepancies, but fewer articles and long words (Pennebaker & King, 1999). Such language is especially common in high attachment and involvement situations (Borelli et al., 2011; Mehrabian, 1967). Mobile devices enable continuous, immediate communication that overcomes spatial and temporal constraints and helps address contextual search tasks, so mobile reviewers tend to be very involved in the situation (Okazaki & Mendez, 2013). The ubiquity of mobile devices also allows users to communicate in motion, anywhere, anytime, leading to highly personal relationships between users and their devices (Shankar et al., 2010). Thus, verbal immediacy should be higher for mobile than for non-mobile reviews.

H3: Mobile customer reviews feature greater verbal immediacy than non-mobile customer reviews.

Bradac, Bowers, and Courtright (1979) claim that verbal immediacy positively influences receivers' judgments of a source's competence, by serving as a proxy for the communicator's positive affect. It also can signal familiarity between communication partners (Bazarova, Taft, Choi, & Cosley, 2012), and it tends to be employed in informal rather than formal or task-oriented situations (Pennebaker &

King, 1999). Thus, the use of verbal immediate language is highly context specific. Encoding this communication content requires communication partners to be experientially connected to the verbalized material (Borelli et al., 2011). In a review setting, potential recipients usually search for objective information about products or companies and have limited experiences with the reviewed object. Therefore, reviews displaying higher verbal immediacy may be less valuable to them, compared with reviews with lower verbal immediacy.

H4: Recipients perceive customer reviews as less helpful when their verbal immediacy is greater.

3.2.3 Empirical Context

The tests of the proposed hypotheses rely on data from the former German opinion and recommendation platform Qype, which was acquired by Yelp in October 2012. Registered users could write reviews about local businesses and institutions in various categories, anonymously with a pseudonym. The platform used a five-star rating scale and allowed reviewers to write a review of any length, either on the website or, since April 2009, through a mobile application. It then tagged mobile reviews with a symbol, to promote its mobile application. Registered users could compliment other users' reviews, but only through the website, not when using the mobile application. Thus, compliments can be assigned unambiguously to recipients using a non-mobile channel, which provides a means to exclude the potential confounding effects caused by the device used to read the review that otherwise would have been unobservable.

3.2.4 Data Collection

The real reviews, collected from a public website, were analyzed on an individual basis (Chen & Lurie, 2013; Ludwig et al., 2013; Lurie et al., 2014; Wu, 2013). The platform maintains an application programming interface that enabled the collection of review texts, ratings, check-ins, timestamps, and information about reviewers and reviewed locations. An automated software agent also crawled the website content to gather mobile tags, that is, information about whether a review had been written with the mobile app. The initial sample included 315,648 customer reviews, written between March 26, 2006, and June 3, 2012. Applying a criterion that requires users

to have generated reviews using mobile and non-mobile devices (i.e., switched devices at least once) produced a subsample of 60,900 reviews by 5,344 users. This criterion reduced reviewer-specific effects, which might reflect different usage behaviors by people who only use one device (mobile or desktop) (Lurie et al., 2014). In the initial sample, only 21.5% reviews were written on mobile devices; the more balanced subsample features 40.4% mobile and 59.6% non-mobile reviews. The reviews referred to 60,647 unique locations in 12 categories, and the restaurant category yielded more than one-third of the total number of reviews.

3.2.5 Real-Time Assumption

To confirm that users create reviews on their mobile devices in real time, the present study gathered check-in time data, as a proxy for the moment of the service experience. Similar to other social media applications (e.g., Foursquare, Facebook Places), check-ins allow users to indicate on their mobile devices (but not non-mobile devices) that they have entered a specific location. Users also can check in independently of a review, such that they visit, check in, then leave and write a review afterward (using a mobile or non-mobile device) about their experiences. To determine how often this was the case, 13,333 collected check-ins were merged with the subsample of collected consumer reviews to define the temporal distance between the check-in time and the time of review creation, according to their respective timestamps. If multiple check-ins appeared, this study used the closest temporal distance between timestamps. The results of this merger showed that 26.3% of the matched reviews were written before a check-in and 73.3% after a user checked in to a place. Among the latter, 55.0% were created on mobile devices and 45.0% on non-mobile devices. Of all mobile reviews, consumers wrote 54.2% within an hour of their check-in, and 81.9% within 24 hours. In contrast, consumers generated less than one-third (30.1%) of the non-mobile reviews within 24 hours of their check-in, and only 2.0% within the first hour. Considering just the first week after a check-in, to reduce bias due to outliers, the mean temporal distance between check-in and mobile review creation was 9.03 hours (SD = 25.05), whereas that for non-mobile reviews was 44.91 hours (SD = 45.75), yielding a significant difference ($t(3{,}759) = 38.36$, $p < .001$). This initial empirical evidence suggests that users write mobile reviews sooner after a service experience than non-mobile reviews, thus

confirming the real-time assumption proposed by Hennig-Thurau et al. (2010) and Lurie et al. (2014), but not empirically tested so far.

3.2.6 Measures

Mobile. To assess whether a review was written with a mobile device, the analysis includes a binary variable (1 = mobile, 0 = non-mobile). Mobile means the review was written in the mobile application; non-mobile indicates it was written with the browser version of the platform.

Perceived helpfulness. Qype users could value a review because it is "useful," "funny," or "well written," confirms their existing ideas, or makes them seek "more like this." Readers saw the total number of compliments without further distinction; this study uses this total number as a proxy for perceived helpfulness.

Review characteristics. The analyses of the consumer reviews relied on the German dictionary in the Linguistic Inquiry and Word Count (LIWC) text analysis program (Pennebaker, Booth, & Francis, 2007; Wolf et al., 2008).[2] This program quantifies the proportion of words in a text that belong to predefined linguistic or psychometric categories and informs assessments of writing styles in many prior marketing, management, and consumer research studies (e.g., Barasch & Berger, 2014; Ludwig et al., 2013; Yin, Bond, & Zhang, 2014). Tang and Guo (2015) affirm the validity and utility of LIWC for studying eWOM communication too. The German dictionary comprises approximately 7,600 words and word stems, each assigned to one or more of 68 categories. The current study considers several of these categories. Specifically, *function words* reflect the arithmetic mean of all pronouns, articles, prepositions, numbers, and expressions of negation or assent (M = 23.54, SD = 8.84). *Verbal immediacy* is calculated as the arithmetic mean of first-person singular pronouns, present tense verbs, discrepancies (e.g., should, could, but), and the inverse counts of both words with more than six letters and articles (Pennebaker &

[2] Differences between the current study and Lurie et al. (2014) mainly reflect different word classifications between the German dictionary, based on the 2001 English LIWC, and the 2007 English LIWC. Pennebaker et al. (2007) offer empirical evidence of the high correlation between these two versions though, and Wolf et al. (2008) verify strong equivalence between the German and English LIWC 2001 in most linguistic categories. Still, they leave open the question of whether the categories in the German version validly reflect the original psychological constructs.

King, 1999). A higher verbal immediacy score implies that the language style is more personal and immediate (Bazarova et al., 2012) (*M* = -5.42, *SD* = 2.66). To demonstrate the importance of style variables, beyond content criteria, this study also includes Lurie et al.'s (2014) measures in the models. *Review length* is the number of words in each review (*M* = 75.03, *SD* = 93.94). *Affective content* refers to expressions of positive and negative emotions (*M* = 6.60, *SD* = 6.29). The *one-sided sentiment* measure assigns reviews a value of 1 if they contain only positive or only negative emotion words (53.31%) and 0 if they contain no or both emotional sentiments. *Cognitive mechanisms* comprise words that reflect causation, insight, inhibition, discrepancy, tentativeness, or certainty (*M* = 8.18, *SD* = 5.74). The measure of *current concerns* counts words referring to jobs, achievement, leisure, home, or money (*M* = 6.25, *SD* = 6.15). *Social processes* reflect the concerns of the reviewer about others, expressed by words that refer to communication or others, such as friends or family, not to the self. The code for *negative valence* applies for ratings that assign one to three stars (28.71%), and otherwise it is positive. Finally, *rating extremity* is operationalized as a binary variable, such that a very bad (1) or very good (5) rating earns a value of 1 (51.48%), and all other ratings take a value of 0.[3]

3.2.7 Control Variables

To control for further review-, reviewer- and location-specific characteristics associated with the review that might influence recipients' appraisals, this study includes a set of covariates. Older reviews have had more time to attract compliments from other community members, so this analysis includes *review age* (Chen & Lurie, 2013; Lurie et al., 2014). It is the number of days between the actual date of review creation and the last day of the data collection. *Reviewer experience* is operationalized as the total number of written reviews per user. The total number of reviews about each place is included as *place publicity*. Including *category-specific fixed* effects helps account for the different categories (12 unequivocal, 1 "other" category to refer to places that could be classified into different categories simultaneously) in the data set. Thus, 13 category dummies were created. To control

[3] The five-star rating scale deviates from the four-point scale in Lurie et al. (2014).

for positive skew, the review age, reviewer experience, and place publicity variables were log transformed.

Multicollinearity should not be a threat in this study, because (1) none of the variables correlated very highly (maximum = .41); (2) the average tolerance value was greater than .10 (M = .77; minimum = .30); and (3) the maximum variance inflation factor was well below the threshold of 10.0 (M = 1.48; maximum = 3.32) (Hair, Black, Babin, & Anderson, 2013).

3.2.8 Specification

The test for differences between mobile and non-mobile reviews relied on mean comparisons. The variances are unequal for the two groups, which calls for the Satterthwaite corrected t-test. The model of perceived helpfulness uses a zero-inflated negative binomial regression, because the count of compliments in the data is skewed toward zero (69.1% of all observations in the sample received no compliments, and among observations with compliments 29.9% received one). In addition to these excessive zeros, the variance (188.92) of compliments clearly exceeds the mean (3.08), suggesting the need for a negative binomial regression (Greene, 2012). Zero-inflated negative binomial regression models can jointly estimate a logistic regression with predictions for the probability for attracting zero compliments and a negative binomial regression that estimates the effects of the proposed content and style characteristics on perceived helpfulness. Because this study seeks to identify the effect of content and style characteristics on perceived helpfulness, this discussion focuses on the negative binomial regression results. The model is specified as:

$$
\begin{aligned}
&\text{perceived helpfulness}_{ijkl} = \\
&\exp\,[\alpha_0 + \beta_1(\text{mobile}_i) + \beta_2(\text{review length}_i) + \beta_3(\text{affective content}_i) \\
&+ \beta_4(\text{one-sided sentiment}_i) + \beta_5(\text{cognitive mechanism}_i) \\
&+ \beta_6(\text{current concerns}_i) + \beta_7(\text{social processes}_i) \\
&+ \beta_8(\text{negative valence}_i) + \beta_9(\text{rating extremity}_i) \\
&+ \beta_{10}(\text{function words}_i) + \beta_{11}(\text{verbal immediacy}_i) + \Omega'_{ijk}Y_{ijk} + \alpha_l + \varepsilon_{ijkl}],
\end{aligned}
$$

where i refers to the review; j is the reviewer; k indicates the location; l is the category; Y_{ijk} is the vector of review-, reviewer-, and location-specific controls; α_l represents category dummies; and ε_{ijkl} is the error term.

3.2.9 Results

Mean comparisons. Table 2 contains the results for the mean comparisons of content and style criteria across mobile and non-mobile reviews. Mobile reviews use fewer function words (M_{mobile} = 21.90, $M_{\text{non-mobile}}$ = 24.65, t(40,749) = -35.73, p < .001) and are more personal and verbally immediate (M_{mobile} = -5.34, $M_{\text{non-mobile}}$ = -5.48, t(44,456) = 6.05, p < .001), in support of H1 and H3. The content characteristics also differ significantly between mobile and non-mobile reviews. In particular, mobile reviews are shorter (M_{mobile} = 43.89, $M_{\text{non-mobile}}$ = 96.18, t(56,971) = -78.48, p < .001), more affective (M_{mobile} = 7.94, $M_{\text{non-mobile}}$ = 5.68, t(37,428) = 40.50, p < .001), more one-sided in their use of positive or negative sentiments (M_{mobile} = .58, $M_{\text{non-mobile}}$ = .50, t(53,336) = 19.53, p < .001), more cognitive (M_{mobile} = 8.45, $M_{\text{non-mobile}}$ = 7.99, t(40,434) = 9.01, p < .001), more focused on current concerns (M_{mobile} = 6.66, $M_{\text{non-mobile}}$ = 5.97, t(41,295) = 12.93, p < .001), less socially focused (M_{mobile} = 4.00, $M_{\text{non-mobile}}$ = 4.51, t(43,993) = -14.74, p < .001), and more negative in their ratings (M_{mobile} = .31, $M_{\text{non-mobile}}$ = .27, t(51,699) = 8.64, p < .001). However, there is no evidence that mobile reviews are less extreme in their ratings (M_{mobile} = .52, $M_{\text{non-mobile}}$ = .51, t(60,898) = .92, p = .357).

Perceived helpfulness. Table 3 offers the results of the negative binomial regression models. The analysis follows a stepwise approach, starting with the baseline models of Lurie et al. (2014) (mobile dummy, Model 1; content-specific measures and review age, Model 2). Model 3 includes further controls for reviewer-, location-, and category-specific effects; Model 4 adds the proposed style variables, function words, and verbal immediacy.

Table 2.

Mean Comparison of Review Characteristics between Mobile and Non-Mobile Reviews (Study 2-I)

	Total (N = 60,900)		Mobile reviews (N = 24,629)		Non-mobile reviews (N = 36,271)			
	Mean	*SD*	Mean	*SD*	Mean	*SD*	*t*-Value[a]	*r*
Perceived helpfulness	3.08	10.91	0.53	2.85	4.81	13.67	$t(40{,}802) = -57.72^{***}$	.27
Review length	75.03	93.94	43.89	54.89	96.18	108.0	$t(56{,}971) = -78.48^{***}$	.31
Affective content	6.60	6.29	7.94	7.78	5.68	4.82	$t(37{,}428) = 40.50^{***}$	.20
One-sided sentiment	.53	.50	.58	.57	.50	.50	$t(53{,}336) = 19.53^{***}$	.08
Cognitive mechanism	8.18	5.74	8.45	6.89	7.99	4.78	$t(40{,}434) = 9.01^{***}$	.04
Current concerns	6.25	6.15	6.66	7.30	5.97	5.22	$t(41{,}295) = 12.93^{***}$	.06
Social processes	4.31	4.02	4.00	4.58	4.51	3.57	$t(43{,}993) = -14.74^{***}$	.07
Negative valence	.29	.45	.31	.46	.27	.45	$t(51{,}699) = 8.64^{***}$	.04
Rating extremity	.51	.50	.52	.50	.51	.50	$t(60{,}898) = 0.92$	.00
Function words	23.53	8.84	21.90	10.47	24.65	7.34	$t(40{,}749) = -35.73^{***}$	.17
Verbal immediacy	-5.42	2.66	-5.34	3.02	-5.48	2.39	$t(44{,}456) = 6.05^{***}$	.03
Review age (in days)	440.2	429.1	302.2	239.1	533.9	498.7	$t(55{,}594) = -76.47^{***}$	.31
Reviews per user	61.55	111.90	36.12	66.83	78.81	131.40	$t(54{,}984) = -52.63^{***}$	.22
Reviews per location	4.21	9.77	4.37	10.00	4.10	9.61	$t(51{,}479) = 3.33^{***}$	.01

[a] As variances are unequal for both groups the Satterthwaite corrected *t*-test is adapted.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 3.

Zero-Inflated Negative Binomial Regression on Perceived Helpfulness (Study 2-I)

		Model 1		Model 2		Model 3		Model 4	
		Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*
Mobile	β_1	-1.791*** -54.710***	.033	-0.968*** -32.378***	.030	-0.621*** -22.457***	.028	-0.621*** -22.425***	.028
Review length (words/100)	β_2			0.574*** 37.701***	.015	0.436*** 37.210***	.012	0.4275*** 36.162***	.012
Affective content	β_3			-0.050*** -16.052***	.003	-0.020*** -6.656***	.003	-0.019*** -6.225***	.003
One-sided sentiment	β_4			0.017 0.711	.024	-0.048* -2.238*	.022	-0.047* -2.200*	.022
Cognitive mechanism	β_5			-0.020*** -7.056***	.003	-0.012*** -4.466***	.003	-0.008** -2.771**	.003
Current concerns	β_6			-0.029*** -10.900***	.003	-0.019*** -7.698***	.003	-0.019*** -7.682***	.003
Social processes	β_7			0.002 0.418	.004	0.004 1.214	.003	0.004 1.037	.004
Negative valence	β_8			-0.365*** -13.219***	.028	-0.281*** -11.558***	.024	-0.285*** -11.644***	.025
Rating extremity	β_9			-0.068** -2.730**	.025	0.073*** 3.347***	.022	0.071** 3.246***	.022

(continued)

(continued)

		Model 1		Model 2		Model 3		Model 4	
		Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*
Function words	β_{10}							0.006*** 3.348***	.002
Verbal immediacy	β_{11}							-0.015** -3.011**	.005
Controls									
Review age (log)				0.366*** 50.037***	.007	0.358*** 47.683***	.008	0.356*** 47.466***	.008
Reviews per user (log)						0.719*** 76.635***	.009	0.716*** 75.702***	.010
Reviews per location (log)						0.076*** 6.157***	.012	0.078*** 6.280***	.012
Category fixed effects						included		included	
Model fit statistics									
Log-likelihood		-89,781		-83,909		-77,617		-77,604	
Pseudo-R^2		.034		.096		.165		.165	
Bayesian information criterion		179,617		168,072		157,676		157,692	
N		60,900		60,900		60,882		60,882	

* $p < .05$. ** $p < .01$. *** $p < .001$.

In both baseline models, mobile reviews exhibit a significant negative effect on perceived helpfulness (Model 1 β_1 = -1.791, $p < .001$; Model 2 β_1 = -0.968, $p < .001$). Adding reviewer- and location-specific controls reduces the negative mobile effect (β_1 = -0.621, $p < .001$), increases McFadden's pseudo *R*-squared (Model 2 = .098; Model 3 = .155), and decreases the Bayesian information criterion (Model 2 = 168,072; Model 3 = 157,676), which confirms the importance of the suggested covariates. In Model 4, function words and verbal immediacy both significantly influence the perceived helpfulness of a review, supporting their inclusion in the analysis. Function words increase perceived helpfulness (β_{10} = 0.006, $p < .001$), in support of H2. Higher verbal immediacy decreases this perception (β_{11} = -0.015, p = .003), in line with H4. However, the effect of mobile reviews on perceived helpfulness remains significantly negative (β_1 = -0.621, $p < .001$). Model 4 also offers significant evidence of a positive effect of review length (β_2 = 0.428, $p < .001$) and rating extremity (β_9 = 0.071, $p < .001$), such that one- or five-star ratings increase perceived helpfulness. All other content variables have negative effects. Specifically, increases in affective content (β_3 = -0.019, $p < .001$), one-sided sentiments (β_4 = -0.047, p = .028), cognitive mechanisms (β_5 = -0.008, p = .006), and current concerns (β_6 = -0.019, $p < .001$) decrease perceived helpfulness, as does negative valence (β_8 = -0.285, $p < .001$).[4] No significant results emerge for the relationship between socially focused language and perceived helpfulness.

The tests of the models with *z*-standardized variables provide basically identical results. The estimates with a negative binomial regression provide results in the same direction, but the Vuong test of both distributions reveals V = 23.275 (Model 4, $p < .001$), such that the zero-inflated negative binomial regression fits better than the negative binomial regression (Greene, 2012). The Lagrange multiplier score (Model 4, $\chi^2(1)$ = 19,876, $p < .001$) for the zero-inflated model with the dispersion parameter fixed at zero confirms overdispersion and the decision to use a zero-inflated negative binomial model, not a zero-inflated Poisson model (Greene, 2012).

[4] An additional analysis with an ordinal rating scale (1 = worst and 5 = best rating) confirms that perceived helpfulness increases with an increase in the rating. Following Wu (2013) and adding the quadratic term of a mean-centered rating scale, instead of the binary extremity variable, also confirms the positive impact of extreme ratings.

3.2.10 Discussion

Mobile reviews are different from non-mobile reviews, and they are perceived differently by recipients. Study I shows that the peculiarities of mobile devices influence not just the use of content elements (Lurie et al., 2014) but also a review's writing style. The cognitive costs of text creation on mobile devices forces mobile reviewers to focus on content instead of style, such that they use fewer functions words. In line with the empirically confirmed real-time assumption, mobile reviews also display higher verbal immediacy, with more personal, direct expressions about the review topic. These style elements thereby help explain why readers perceive reviews as less or more helpful, which represents a contribution to recent research on style elements in customer reviews (Ludwig et al., 2013; Schindler & Bickart, 2012). Recipients value reviews that delineate the review situation by clarifying the relationship of the sender to the topic and the relationship among the content elements, using function words. In contrast, recipients discount reviews that use verbal immediate language, which appears context specific and requires prior knowledge of the reviewed topic. Whereas Lurie et al. (2014) find that content variables are rarely significant, most of the mobile-specific content characteristics in Study I negatively influence perceived helpfulness.

Although the inclusion of style-specific criteria provides a more fine-grained picture of the helpfulness of review elements, it cannot fully explain why mobile reviews are less valued than non-mobile reviews. Factors beyond measurable content and style differences, as well as beyond reviewer-, review-, location-, and category-specific elements, obviously could influence recipients' perceptions of mobile reviews. The mere identification of the device used to write the review appears to offer a cue for recipients' judgments of the helpfulness of a review.

Previous research on social cues suggests that people process source cues heuristically, such that they influence the appraisal of communication content (Chaiken & Maheswaran, 1994; Menon & Blount, 2003). Recipients use source cues to evaluate the helpfulness of a review, based on the similarity they recognize between their own identity and the identity of the reviewer, as disclosed by the source cue (Forman et al., 2008; Naylor et al., 2011; Racherla et al., 2012). Reviews seem valuable to recipients only if they share a similar identity with the reviewer

(Forman et al., 2008; Naylor et al., 2011). Forman et al. (2008) show for example that reviews that disclose the geographical location of a reviewer influence product sales in that region. Naylor et al. (2011) also demonstrate that a completely anonymous review is more helpful than a review written by reviewer who is obviously dissimilar from the recipient. Such social cues might stem not only from biographical information but also from any other information that induces comparisons between the recipient and the reviewer, including cues of the devices used. On the focal platform, only non-mobile users evaluate reviews, so the device they used to consume the review differed from the device used to generate mobile reviews. In turn, they may have discounted the helpfulness of a mobile review, due to the perceived dissimilarity between devices.

However, the field study cannot confirm whether the device tag works as a source cue. Therefore, Study II is a scenario-based, online experiment that holds the content and style of a review constant while manipulating the device tag, to test recipients' judgments of mobile and non-mobile reviews, according to the congruency of the devices used to generate and to read the review.

3.3 Study II: Perceived Compatibility with Review Device and Causal Attributions

3.3.1 Theoretical Background and Hypotheses Development

Previous research into source cues mainly uses social identity theory to explain why recipients perceive reviews written by reviewers with a similar identity as more valuable (Forman et al., 2008; Naylor et al., 2011; Racherla et al., 2012). The basic premise is that people strive to belong to groups that share the same values (in-group) and whose members are distinct from those of another group (out-group) (Tajfel & Turner, 1979). Customer reviews then may be more helpful to recipients if both parties share source-related characteristics, because then recipients perceive themselves as similar to the reviewer in preferences and backgrounds (Naylor et al., 2011; Racherla et al., 2012). When a review platform implements a device tag, it therefore might encourage recipients to compare themselves to the reviewer, on the basis of the device used to generate the review.

Technology acceptance and innovation adoption research indicates that the perceived compatibility of a technology "with the existing values, needs, and past experiences" of the adopter is an important determinant of acceptance (Moore & Benbasat, 1991, p. 195). Such theory implies that review recipients also might assess their similarity to the reviewer according to their perceptions of the compatibility with the reviewer's device. Thus, compatibility considerations are context specific (Karahanna, Agarwal, & Angst, 2006), in the sense that recipients judge the compatibility with the reviewer's device based on the own device.

This prediction also is in line with the self-categorization approach in social identity theory (Turner, Oakes, Haslam, & McGarty, 1994). Even if people embrace different social identities (e.g., mobile user, non-mobile user), they use the identity that is most salient in any given situation. This self-categorization process is flexible and constructive, so the salience of an identity is highly context dependent. Recipients sitting in front of a non-mobile device reading a review therefore should base their compatibility judgments on their identity as non-mobile user, which is highly salient to them in that situation. In turn, these recipients should evaluate reviews written on a mobile device as less compatible with their own values and needs than a review written on a non-mobile device would be, which in turn prompts a poorer assessment of the helpfulness of the review.

H5: Reviews written on a mobile device have a negative effect on (a) perceived compatibility, which (b) hinders perceived helpfulness, such that these reviews (c) have indirect negative effects on perceived helpfulness, mediated by perceived compatibility.

A question that remains though is why social cues and shared social identity increase the perceived helpfulness of customer reviews. Existing evidence of attribution behavior indicates that recipients make inferences about cause-and-effect relationships when they lack information about the specific review situation (Chen & Lurie, 2013; He & Bond, 2015; Sen & Lerman, 2007). They attribute information and its accuracy either internally, to reviewers and their personal disposition, or externally, to the reviewed object (Sen & Lerman, 2007). The specific attribution path depends on the perceived level of independence between the reviewer and the review. If a recipient judges the review as detached from the specific reviewer, such

that it could have been created by anyone, he or she likely attributes the motivation for the review externally, to the focus of that review (Jones & Davis, 1965; Kelley, 1973). Attribution and social identity theory both indicate that the correspondence between an observer and an actor is a good predictor of external attribution, because the actor's behavior will be consistent with the observers' expectations (Jones & Davis, 1965; Oakes, Turner, & Haslam, 1991). These expectations also are biased toward the self, in that observers expect their attitudes and values to be shared (Naylor et al., 2011; Ross, Greene, & House, 1977). If recipients notice that the reviewers' attitudes actually deviate from their own, they likely attribute these deviations to the reviewers' personal dispositions (Ross et al., 1977).

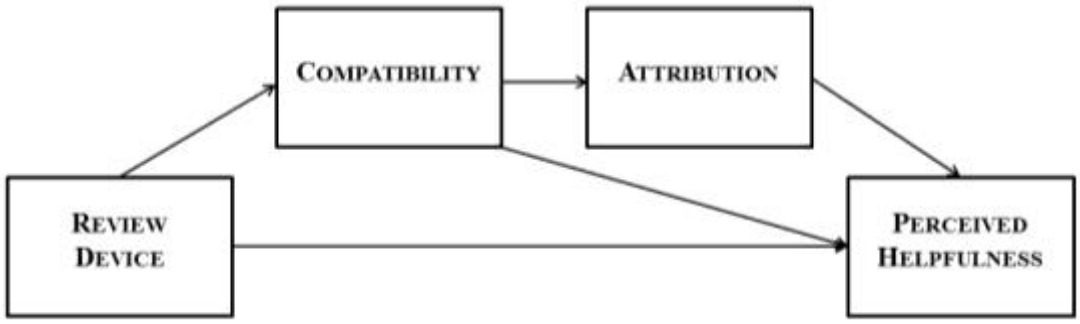
Therefore, perceived incompatibility of a device used to write a review with the recipient's own attitudes and values should produce an internal attribution for the review, such that it appears inconsistent or person-specific. In contrast, perceived compatibility should drive external attributions, because the reviewer's action (writing a review on a compatible device) is consistent with the recipient's expectations. With these distinct attributions, recipients should evaluate the helpfulness of customer reviews differently. Specifically, according to attribution theory, recipients will perceive messages as less helpful if they attribute them to internal dispositions rather than external stimuli (Eagly, Wood, & Chaiken, 1978). Sen and Lerman (2007) and Chen and Lurie (2013) confirm this discounting principle for customer reviews, showing that reviews attributed to the topic (i.e., product or service) are considered more helpful than reviews attributed to the reviewer. Therefore, perceived compatibility should have an indirect effect on perceived helpfulness, through the recipient's attributions.

H6: Perceived compatibility leads the recipient to (a) attribute the reviewer's motivation externally (i.e., review subject's quality) rather than internally (i.e., reviewer's disposition), which then (b) enhances perceived helpfulness, such that this perception has (c) a positive indirect effect on perceived helpfulness, mediated by recipients' attributions.

3.3.2 Study Goal and Design

To test the proposed relationship among compatibility considerations, attributions, and perceived helpfulness (Figure 2), this study adopts a between-subjects experimental design online, with a scenario technique and subsequent online survey.

Figure 2.
Relationship of Review Device, Compatibility, Attribution, and Perceived Helpfulness (Study 2-II)



In accordance with the field study, this experiment manipulates the device the reviewer used (mobile vs. non-mobile), to assess the effect on perceptions among non-mobile recipients. In December 2013, a professional market research firm helped recruit participants. Similar to the field study, only desktop users could rate review helpfulness, so only non-mobile users were invited to participate. These participants were randomly assigned to the two experimental conditions. The scenario described a situation in which they already had decided to meet some friends at a new Italian pizzeria, but before going there, they checked the quality of the restaurant by reading online reviews on a customer opinion platform. The scenario described the visitation decision as already made, because previous research indicates that customers already committed to a choice process individual reviews rather than aggregated, average ratings or the total number of reviews (Pan & Zhang, 2011; Weinberg & Davis, 2005). Next, the scenario introduced a fictitious user who had already visited the pizzeria and wrote a review. In both conditions, the review text was the same. However, in the first condition, the review was tagged with a mobile symbol, indicating that it had been written on a mobile device. In the second condition, the review was tagged with a desktop computer symbol, indicating it had

been created on a non-mobile device. The tagging mimicked the real mobile symbol used on the customer opinion platform from Study I. To strengthen the manipulation and guarantee comparability between conditions, the non-mobile devices also were tagged, even though the real platform does not provide this explicit information. Furthermore, a text instruction noted that the reviews had been written on either a mobile device or a desktop computer. The other review features (text, rating, user name, user's number of reviews, date of creation) remained constant.

To check that participants read the scenario and thus had the chance to be primed by the treatment, an instructional manipulation check (IMC; Oppenheimer, Meyvis, & Davidenko, 2009) appeared at the end of the scenario. It asked participants to click on a picture before clicking the continue button, which forwarded them to the online survey. If participants failed the IMC, they were excluded. Those who passed the IMC, continued on to the online survey, and answered questions about their perceived situational compatibility with the reviewer, attributions of the reviewer's motivation, and perceived helpfulness of the review. To ensure that participants in each condition noticed the device used to write the review, they also indicated if the review was written on a mobile or non-mobile device. The survey also included measures of the control variables and a realism check.

Of the 754 initial participants recruited, 342 passed the IMC. Subsequently, participants that failed the manipulation check regarding the device used to write the review (81 of 342) also were excluded. Quality checks, with regard to the speed of completion and missing answers, excluded another 36 participants. Thus the final sample consisted of 225 valid, usable observations. To guarantee comparability to the field study, all respondents completed the survey on a desktop or laptop computer, not on a mobile device.

3.3.3 Measures

To assess the dependent variable, *perceived helpfulness*, participants rated the review on an adapted version of a helpfulness scale (Sen & Lerman, 2007; Wu, 2013) that includes four semantic differential response items (coefficient $\alpha = .93$) and uses a 7-point scale ("very useful–not at all useful," "very accurate–not at all accurate," "very informative–not informative at all," and "very helpful–not at all helpful"). The

measure of the *compatibility* of the recipient with the device used by the reviewer was adapted from an innovation adoption study (Moore & Benbasat, 1991). Respondents in both conditions indicated whether that specific review, written on a mobile device or desktop computer, (1) was compatible with their lifestyle, (2) was congruent to their own needs, and (3) fit the way they were used to dealing with such things. All items (coefficient $\alpha = .93$) were measured on a 7-point Likert scale (1 = "strongly disagree," 7 = "strongly agree"). In line with Sen and Lerman (2007), *attributions* about the reviewer's motives were measured separately for the internal and external options. For the external attribution measure (coefficient $\alpha = .87$), respondents completed a 7-point Likert scale about the extent to which they agreed that (1) the review accurately reflected how good the pizzeria is, (2) the motive for the reviewer to write this review was to inform other customers accurately about the quality of the pizzeria, and (3) the reviewer's evaluation was based on true experiences and feelings. Then internal attribution was measured as a single item on the same scale, asking respondents whether other reasons, having nothing to do with the quality of the pizzeria, influenced the reviewer's opinion. Similar to Chen and Lurie (2013), the calculation of the causal score subtracted internal from external attributions, such that higher values implied more external and less internal attributions.

The respondents' ratio of mobile and non-mobile Internet usage served as covariates. Participants indicated on a slider whether they primarily used a mobile device or non-mobile devices like desktops or laptops to go online. Lower scores indicated predominantly mobile Internet usage, and higher scores signaled predominantly non-mobile Internet usage. Finally, the survey collected sociodemographic variables: gender (female = 1; male = 0), age, and education (higher education = 1; lower education = 0).

The realism check included two items ("The scenario described was realistic" and "I had no difficulty imagining myself in this situation"), with a 7-point Likert scale (1 = "strongly disagree," 7 = "strongly agree"; Dabholkar, 1994). All the original scales were in English, but the online survey was in German, so back translation ensured their equivalence (Brislin, 1970). The correlations between the constructs were acceptable (see Table 4).

Table 4.

Mean Comparison and Correlation of Compatibility, Attribution, and Perceived Helpfulness (Study 2-II)

	Mobile written (N = 115)		Non-mobile review (N = 110)			Correlation matrix		
	Mean	*SD*	Mean	*SD*	*t*-Value	Mobile	Compatibility	Attribution
Compatibility	3.922	1.796	4.676	1.607	$t(223) = -3.313$***	-.217***	1	
Attribution	1.504	2.370	1.439	2.506	$t(223) = 0.200$	.013	.287***	1
Perceived helpfulness	5.144	1.304	5.171	1.214	$t(223) = -0.160$	-.011	.283***	.569***

* $p < .05$. ** $p < .01$. *** $p < .001$.

3.3.4 Results

Participants considered the scenario realistic ($M_{realismitem1}$ = 5.27; $M_{realismitem2}$ = 5.28), without any significant differences between both treatment groups, $t_{realismitem1}(223)$ = -0.082, p = .935, and. $t_{realismitem2}(223)$ = -1.095, p = .275. The test of the proposed conceptual framework involved two separate mediation models using the PROCESS procedure (Hayes, 2013). The first mediation model included the device tag as the independent variable (0 = non-mobile, 1 = mobile), compatibility with the review device as a mediator, and perceived helpfulness as the dependent variable (Model 4, Hayes, 2013), along with the mobile-to-desktop usage ratio, age, gender, and education as covariates, in an attempt to test the social cue assumption (H5). Bootstrapping with 10,000 samples was used to assess indirect effects (Preacher & Hayes, 2008). The results in Table 5 (Model I) show that the device has a significant direct effect on perceived compatibility, a(I) = -0.727, $t(219)$ = -3.212, p = .002. The non-mobile participants felt less compatible with the review generated on a mobile device, in support of H5a. Compatibility with the device instead has a significant positive effect on perceived helpfulness, b(I) = 0.205, $t(218)$ = 4.236, p < .001. That is, in line with H5b, the more compatible a recipient feels with the reviewer's device, the more helpful the review seems. Testing for the indirect effect of the device tag on perceived helpfulness through compatibility yields a significant negative effect, a(I) × b(I) = -0.149, 95% confidence interval (CI) [-0.284, -0.055]. As predicted by H5c, compared with non-mobile recipients who confronted a non-mobile review, those who read a mobile review perceived it as less helpful, due to their perception of device incompatibility.

The second mediator model (Table 5, Model II), with compatibility as the independent variable, attribution as a mediator, perceived helpfulness as the dependent variable, and the same covariates, tests whether attribution theory can explain why social cues and a shared social identity increase the perceived helpfulness of customer reviews. As proposed in H6a, compatibility with the device has a significant positive effect on attribution, a(II) = 0.433, $t(219)$ = 4.738, p < .001. A more compatible device, matching the values and needs of the recipient, leads that recipient to attribute the motivation for the review externally to the reviewed topic. Attribution has a positive effect on perceived helpfulness, b(II) = 0.284, $t(218)$ = 9.717, p < .001, confirming H6b. The more a review is attributed externally, the

higher the perceived helpfulness. The indirect effect of compatibility, through attribution, on perceived helpfulness is positive and significant, a(II) × b(II) = 0.123, 95% CI [0.070, 0.183], as suggested in H6c. Relative to those who feel less compatible with the reviewer's device, those who are more compatible perceive the review as more helpful, because they attribute the motivation for the review to the reviewed subject, not the reviewer.

As an additional analysis, a multiple mediator model in serial (Model 6, Hayes, 2013), with the device tag as an independent variable, compatibility as a first mediator, attribution as a second mediator, perceived helpfulness as the dependent variable, and the same covariates (Table 5, Model III), tests for the overall effect of the device tag on perceived helpfulness. The indirect effect of the device on perceived helpfulness, through compatibility and attribution, is negative and significant, a_1(III) × d_{21}(III) × b_2(III) = -0.094, 95% CI [-0.175, -0.038]. Relative to those who read a non-mobile review, those who read a mobile review rate it less helpful, because they feel less compatible with the review device, which leads them to attribute the review to internal reasons, involving the reviewer rather than the topic.

Table 5.

Regression Coefficients, Standard Errors, and Model Summary Information for (Multiple) Mediator Models (Study 2-II)

		Model I				
		M (Compatibility)			Y (Helpfulness)	
		Coeff.	*SE*		Coeff.	*SE*
X(I) (Mobile = 1, non-mobile = 0)	a(I)	-0.727**	.226	*c'*(I)	0.173	.166
M(I) (Compatibility)		-----	-----	*b*(I)	0.205***	.048
Constant	i_1(I)	5.720***	.502	i_2(I)	4.703***	.453
Covariates						
Mobile-to-desktop usage ratio		-0.027*	.013		0.002	.010
Age		-0.084	.077		-0.117*	.055
Gender (male = 0, female = 1)		0.035*	.237		0.074	.170
Education (low = 0, high = 1)		0.232	.233		-0.194	.167
		R^2 = .089			R^2 = .107	
		F(5, 219) = 4.267**			*F*(6, 218) = 4.338***	

	Effect	*SE*	*LLCI*	*ULCI*
Indirect effect of (mobile) device on helpfulness through compatibility (I)	-0.149	.059	-0.284	-0.055
Total effect of (mobile) device on helpfulness (I)	0.024	.168	-0.308	0.355

(continued)

(continued)

		Model II				
		M(II) (Attribution)			Y(II) (Helpfulness)	
		Coeff.	*SE*		Coeff.	*SE*
X(II) (Compatibility)	a(II)	0.433***	.092	c'(II)	0.071	.042
M(II) (Attribution)		-----	-----	b(II)	0.284***	.029
Constant	i_1(II)	-1.598	.852	i_2(II)	5.271*	.372
Covariates						
Mobile-to-desktop usage ratio		0.023	.019		-0.005	.008
Age		0.072	.106		-0.133**	.046
Gender (male = 0, female = 1)		0.387	.328		-0.034	.143
Education (low = 0, high = 1)		0.061	.322		-0.197	.139
		R^2 = .101			R^2 = .374	
		F(5, 219) = 4.937***			F(6, 218) = 21.665***	

	Effect	*SE*	*LLCI*	*ULCI*
Indirect effect of compatibility on helpfulness through attribution (II)	0.123	.029	0.070	0.183
Total effect of compatibility on helpfulness (II)	0.194	.047	0.101	0.287

(continued)

(continued)

		Model III						
		M_1(III) (Compatibility)			M_2(III) (Attribution)			Y(III) (Helpfulness)	
		Coeff.	*SE*		Coeff.	*SE*		Coeff.	*SE*
X(III) (Mobile = 1, non-mobile = 0)	a_1(III)	-0.727**	.226	a_2(III)	0.371	.320	c'(III)	0.068	.139
M_1(III) (Compatibility)		-----	-----	d_{21}(III)	0.456***	.094	b_1(III)	0.076	.043
M_2(III) (Attribution)		-----	-----		-----	-----	b_2(III)	0.283***	.029
Constant	i_{M1}(III)	5.720***	.502	i_{M2}(III)	-1.842*	.877	i_Y(III)	5.225***	.384
Covariates									
Mobile-to-desktop usage ratio		-0.027*	.013		0.024	.019		-0.005	.008
Age		-0.084	.077		0.062	.106		-0.135**	.046
Gender (male = 0, female = 1)		0.035*	.237		0.381	.328		-0.034	.143
Education (low = 0, high = 1)		0.232	.233		0.030	.323		-0.202	.140
		R^2 = .089			R^2 = .107			R^2 = .374	
		F(5, 219) = 4.267**			F(6, 218) = 4.344***			F(7, 217) = 18.538***	

(continued)

(continued)

	Effect	*SE*	*LLCI*	*ULCI*
Indirect effect of (mobile) device on helpfulness through compatibility (III)	-0.055	.038	-0.150	0.002
Indirect effect of (mobile) device on helpfulness through compatibility and attribution in serial (III)	-0.094	.035	-0.175	-0.037
Indirect effect of (mobile) device on helpfulness through attribution (III)	0.105	.090	-0.069	0.286
Total effect of (mobile) device on helpfulness (III)	-0.044	.107	-0.250	0.168

Note. $N = 225$; number of bootstrap resamples = 10,000; *LLCI* = lower-level confidence interval; *ULCI* = upper-level confidence interval.
* $p < .05$. ** $p < .01$. *** $p < .001$.

3.3.5 Discussion

Beyond the content and style characteristics, a simple tag that indicates the device used to write a review can serve as a source cue and influence recipients' perceptions of the review's helpfulness. By reproducing the conditions from the field study (i.e., only desktop recipients may evaluate review helpfulness), this study offers evidence that the level of alignment between the device used to create the review and the device used to read it leads the recipient to perceive a review as helpful or not. Non-mobile recipients discount the helpfulness of mobile reviews, because these reviews are not compatible with their reading situation. The findings also explain this process: When recipients feel compatible with the device used for review creation, they attribute the review's source to the quality of the reviewed subject, rather than to other reasons, such as the reviewer's personal dispositions. As indicated in previous studies (Chen & Lurie, 2013; Sen & Lerman, 2007), attributing the review to the topic is an antecedent of perceptions of a review as helpful. In summary, recipients using non-mobile devices perceive mobile reviews as less helpful, because they do not sense compatibility in their devices and thus attribute the reason for writing the review to personal motivations, not the quality of the review subject.

3.4 General Discussion

3.4.1 Theoretical Contributions

The findings from this study contribute to the existing research in several ways. First, this investigation represents a response to calls for empirical evidence of how mobile technology has changed the creation and reception of eWOM (Berger, 2014; Hennig-Thurau et al., 2010; Shankar & Balasubramanian, 2009). The findings show that the peculiarities of mobile devices invoke a specific mobile writing style, distinct from non-mobile writing styles, elaborating on recent research that notes the influential role of the communication channel on WOM content (Berger & Iyengar, 2013). By testing the content and style characteristics of customer reviews on a multi-category customer opinion platform, the present study also extends and validates evidence provided by Lurie et al. (2014). Mobile-specific linguistic characteristics, such as shorter length, fewer function words and more verbal immediacy, make customer reviews appear less helpful to recipients. In addition, the simple knowledge of what

kind of device the reviewer used to create the review influences recipients' judgments of the review's helpfulness, depending on whether the devices align. The evidence of this "mobile effect," in both field and experimental studies, helps confirm Lurie et al.'s (2014) findings. In extending prior mobile device research that has focused primarily on what motivates consumers to use mobile devices for their eWOM behavior (Okazaki, 2008, 2009; Palka et al., 2009), the current findings add insights into how mobile devices used by consumers for eWOM influence the perceptions of communication partners.

Second, this study elaborates on previous research into the role of source cues. The current findings indicate that recipients use device tags to infer information about the reviewer and compare their identities. This finding is particularly noteworthy because devices offer weak social identifiers; they do not reflect personal dispositions or entrenched background traits (Forman et al., 2008; Naylor et al., 2011). However, it resonates with the minimal group paradigm of social identity theory, in that little, seemingly meaningless information is all that is needed to trigger social identification processes (Billig & Tajfel, 1973). By integrating social identity and attribution theory, this study also helps explain why a shared social identity enhances the perceived helpfulness of a review. Previous conceptualizations have not differentiated the perceptional process of similarity from an attributional process, though these cognitive processes are known to be analytically distinct (Racherla et al., 2012). The current findings indicate that recipients first evaluate their perceived compatibility with the reviewer, in terms of the devices used, and then, on the basis of these compatibility considerations, they attribute the motive for the review to either personal aspects of the reviewer or the subject of the review.

Third, as an extension of the effect of perceived compatibility on technology and innovation usage (Kleijnen et al., 2007; Meuter et al., 2005; Moore & Benbasat, 1991), this study shows that the perceived compatibility of the recipient with the reviewer, according to the devices they use, is critical to the appraisal of the review. People thus assess their compatibility with a technology when evaluating whether to use it but also exhibit compatibility considerations in communication situations in which both the sender and receiver use technologies. Recipients evaluate the technology usage of their communication partner to make social inferences and judge the credibility of the content. Furthermore, the reference point for assessing

compatibility depends not on the personal dispositions of the recipient but on the technology the recipient uses to access that content. This finding expands Karahanna et al.'s (2006, p. 784) finding that compatibility considerations are driven by "reality as it is currently experienced." Such findings are particularly valuable in omnichannel retail settings, with their blurred channel borders that force consumers to address different technologies during single retail experiences (Verhoef, Kannan, & Inman, 2015).

Fourth, this study contributes to research on review helpfulness by introducing two style characteristics that influence the helpfulness of a customer review. Function words and verbal immediacy increase the diagnosticity of reviews by providing additional information about the relationship of the reviewer with the reviewed topic and the review situation, which are not solely conveyed by content elements. Function words contextualize content elements and therefore increase readability and the ability to understand complex relationships (Hartley et al., 2003). Verbal immediacy signals high attachment and involvement (Borelli et al., 2011; Mehrabian, 1967), which in turn causes the review to appear biased or subjective and less helpful. These two style characteristics thus provide a more fine-grained picture of the impact of content and style criteria on perceived helpfulness (Lurie et al., 2014; Schindler & Bickart, 2012; Scholz & Dorner, 2013).

3.4.2 Managerial Implications

Platform managers must acknowledge that mobile reviews differ from non-mobile reviews in terms of their content- and style-specific characteristics, and the content- and style-specific peculiarities of mobile reviews (e.g., fewer words, more affective content) are generally perceived as less helpful. Therefore, platform managers might consider adding systems or guidelines that can improve the linguistic quality of mobile reviews (Scholz & Dorner, 2013), though any such guidelines must reflect the challenges of creating content with mobile devices. In particular, the cognitive costs imposed by small screens and tiny keyboards might limit the possibilities for encouraging more quality, or at least necessitate innovative solutions (e.g., voice commands to increase the number of words).

Platforms also should take caution before tagging content as mobile or non-mobile, because such cues can create boomerang effects if the device used to create the content does not match the device used to consume that content. To avoid this device effect resulting from low perceived compatibility, a viable solution might be to avoid any such device tags, because not disclosing identity-related information about the reviewer is better, in terms of persuasion, than disclosing an identity that is dissimilar. In this case, anonymous reviews perform as well as reviews that disclose a similar identity (Naylor et al., 2011). But reviews do not have to go without a device tag. Another option, based on the findings of the present study that show that recipients assess compatibility on the basis of the devices used, would be to adapt the reviews that a recipient sees dynamically, according to the device that she or he uses to access the platform, such that the devices are always compatible.

3.4.3 Limitations and Further Research

Several limitations of this study suggest avenues for further research. First, this study tested the compatibility considerations of only recipients who used a non-mobile device to read the review, to mimic the field study. Perceptions of incompatibility with the mobile device might stem from the relatively low adoption of mobile devices for content creation though (Ghose & Han, 2011), such that recipients judge mobile content less helpful than non-mobile content. Such an explanation contrasts with current reality though, where consumers create vast amounts of content using mobile devices. The present study also controlled for the adoption of mobile devices by the recipient. Nevertheless, further research might investigate whether recipients who use mobile devices infer compatibility correspondingly, to generalize the findings. The adoption of other channels, such as smartwatches or augmented reality glasses, also could be investigated according to this framework (Lurie et al., 2014).

Second, the experimental study focused on the effect of the device tag on perceived helpfulness by isolating a single review and holding all other factors constant. However, review valance, product type, and the surrounding reviews can all moderate attributional processes (Chen & Lurie, 2013; He & Bond, 2015; Sen & Lerman, 2007). Further research should include these factors in a broader experimental design, to investigate specifically whether these factors moderate attribution behavior after recipients assess their compatibility with the reviewer's

device or already influence those compatibility considerations about the reviewer. Such an investigation could clarify situations in which recipients consider source cues in their evaluation process. Do recipients use source cues simultaneously with the review's informational content to judge the helpfulness of a review, as proposed by the theory of heuristic cues (Chaiken & Maheswaran, 1994)? Or do they consider source cues only when they challenge the credibility of the informational content? For example, recipients might assess their compatibility with the reviewer's device only after reading a positive review that they perceive as subjectively biased (Sen & Lerman, 2007).

Third, the present study did not include pictorial information; no pictures were available. However, images can increase the usability of online reviews (Cheng & Ho, 2015), and mobile devices make it easy for reviewers to take pictures of the service experience during their consumption. Therefore, supplementing the mobile customer reviews with images might increase the perceived helpfulness of mobile reviews and attenuate the negative effects of their text-specific characteristics, in terms of content and style. This mobile-specific feature should be considered in further research.

Fourth, by including verbal immediacy in the analysis of mobile reviews, the authors attempt to capture some context-specific effects of the mobile review situation. However, mobile behavior is very context specific, so further research might try to control other factors in the situational context. For example, do reviewers write during the consumption experience or after it? Do they generate reviews while in transit, at home, or in the office? Limited contextual data are available with regard to mobile communication (Cumiskey & Ling, 2015), so including further linguistic measures, such as temporal contiguities (Chen & Lurie, 2013) or location-based information to gain insights about specific review situations might be a valuable path for further research.

3.5 Conclusion

Sharing consumption experiences in real time with the help of mobile devices has more negative than positive effects on the appraisals of these reviews by other consumers—at least if they are not using a mobile device. Using field data, the

authors demonstrate that beyond the content of a review, recipients discount the style in which mobile reviews are written. Even when controlling for style- and content-specific differences, the simple fact that a review was identified as written on a mobile device negatively influences the helpfulness of that review. By elaborating on this mobile effect in a scenario experiment, the authors also provide evidence that recipients assess their compatibility with the reviewer's device, based on a simple device tag. Only if this device is congruent with the device that recipients use to read a review do they feel compatible and judge the review as helpful, because it can be attributed to the quality of the review subject. However, if recipients feel incompatible, because of differences in the devices used, they attribute the review to the personal dispositions of the reviewer and discount its helpfulness. The results thus challenge the common industry practice of tagging content according to how it was created, which induces a boomerang effect when recipients sense incompatibility with reviewers' devices.

4 The Influence of Mobile Push Notifications on the Success Rate of Customers' Late Bidding

Armin März, Michael Lachner, Jan H. Schumann,
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The present study investigates how mobile push notifications in online auctions can improve late bidding success. Late bidding is a prevalent strategy, in which bidders submit their bids at the very end of an online auction; mobile push notifications remind them of upcoming deadlines anywhere and anytime. This research uses field data to demonstrate that late bidders use these mobile push notifications more frequently than bidders with different bidding patterns. Furthermore, within the group of late bidders, the chance to win an auction increases with their use of such push notifications. After a mobile push notification, late bidders submit their bids not only through mobile devices but also through non-mobile channels. Less experienced late bidders also benefit from push notifications, which increase their success chances. Managers of online (auction) platforms therefore should work to shift perceptions of push notifications: Rather than intrusive, they can be developed as customizable, helpful features.

Keywords: *bidding efficiency; late bidding; mobile device; online auction; push notification*

4.1 Introduction

Last-minute bidding, or sniping, is a prevalent strategy on online auction platforms. Even when their run times last several days, 37% of all observed auctions prompt bids at the very last moment (Ockenfels & Roth, 2006). Bidding in the very last moment is especially popular in auctions with fixed end times ("hard closes") and seems beneficial for consumers (Roth & Ockenfels, 2002). By sniping, consumers in both common value auctions (Bajari & Hortaçsu, 2003) and private value auctions (Ockenfels & Roth, 2006) can disguise their specific valuation for the focal item. For experienced bidders, late bidding thus offers a reasonable strategy to avoid bidding

wars with incremental bidders (Roth & Ockenfels, 2002) or shill bidding by sellers, who seek to boost the auction price inaccurately (Barbaro & Bracht, 2006). However, the actual payoff of sniping relative to that of early bidding strategies appears uncertain. Research offers no evidence of substantial economic payoffs in the final price (Ely & Hossain, 2009) or statistically significant financial benefits of sniping (Gray & Reiley, 2013). These results might arise because in second-price, sealed-bid auctions, the final price depends on the winning bidders' bids, as well as on the second highest bidders' willingness to pay, and the latter information is hidden from snipers. Still, late bidders are more efficient in terms of their auction winning rates than early bidders (Ely & Hossain, 2009; Wenyan & Bolivar, 2008; Yang & Kahng, 2006). If a sniper and an incremental bidder have the same willingness to pay, the former has a strategic advantage, by leaving the latter insufficient time to increase its bid up to its actual willingness to pay.

Sniping also is challenging though, for two main reasons. First, it is associated with substantial coordination costs, such as fees for external sniping tools or the effort to monitor the deadline (Kamins et al., 2011). Second, snipers constantly risk missing deadlines; 90% of polled late bidders reported failures, simply because they were not available at the relevant time (Roth & Ockenfels, 2002). Yet automatic sniping tools cannot satisfy the "ludic value" (Backus, Blake, Masterov, & Tadelis, 2015) of sniping or the "thrill" (Cheema, Chakravarti, & Sinha, 2012) of winning at the last minute. Instead, auction platform providers experiment with interactive features that reduce both monitoring and bidding costs, as well as the risk of missing auctions' deadlines, in an attempt to increase their attractiveness to participants and their profit (Bapna et al., 2004). For example, mobile applications with push notifications on smartphones enable consumers to participate in an auction in the last minutes, anytime and anywhere, with little expense. These interactive mobile apps are useful and easy to use (Shankar et al., 2010), allowing customers to interact with a brand (Kim, Wang, & Malthouse, 2015), such as an auction platform in this case. Many smartphone apps deliver time- or location-sensitive messages through push notifications to the home screens of mobile devices (Warren, Meads, Srirama, Weerasinghe, & Paniagua, 2014), and an auction deadline is one such a time-sensitive reminder that prospective customers can sign up to receive and then react immediately.

Yet to the best of our knowledge, there is no research about the impact of mobile push notifications on bidding behavior in general or last minute bidding in particular, which is surprising, considering the growing importance of mobile devices. Smartphones are omnipresent, with estimated penetration rates of more than 67% in the West in 2015 (eMarketer, 2015). One-third of all e-commerce transactions are generated on mobile devices (Criteo, 2016), and in an online auction context, 43% of gross merchandise volume was transacted through mobile channels in 2015 (eBay, 2016). Mobile participants in online auctions are not tethered to their desktop computers, such that they may be available and prepared to submit a late bid virtually anywhere and anytime.

Therefore, we seek to investigate how mobile push notifications affect late bidding behavior and success. Mobile technology and push notifications likely reduce the effort involved in monitoring auctions and submitting bids in any situation; we investigate the relationship between mobile push notification and late bidding to gain more precise insights. That is, we check for differences in the use of a watch list, which is a required component of the mobile push notifications, between late bidders and bidders who adopt other strategies. Then we compare various uses of mobile push notifications to determine if their use is associated with higher chances of winning with a late bidding attempt. To investigate these research questions, we analyze behavioral and transactional field data from the German marketplace of an online auction platform. Within an initial sample of 83,182 auctions of the most offered products in a three-month period, we identify 60,670 sniping attempts.

The resulting insights into how interactive features influence (late) bidding behavior contribute to literature that has looked at the reasons, risks, and output of late bidding, without addressing supportive features. This study also advances research into interactive decision aids (Häubl & Trifts, 2000), in that we clarify the risk and effort-reducing functions of two popular tools: watch lists and mobile push notifications. For mobile marketing literature, we detail how this form of mobile targeting (Luo, Andrews, Fang, & Phang, 2014) offers a viable application of co-produced, personal media messages to reduce consumers' risk (Bacile et al., 2014). We also consider a genuinely time-sensitive aspect of the customer–firm interaction, moving beyond the predominant focus on location-based applications (Dickinger & Kleijnen, 2008; Fang, Gu, Luo, & Xu, 2015). With this investigation, we gain

knowledge of the interplay among devices and discover that mobile push notifications can affect late bidding through non-mobile channels. Our results confirm the predictors of late bidding success that have been identified in prior research and supplement them with the demonstrated interaction effects with push notifications. Finally, our research can help auction platform providers understand how their customers use several mobile features to organize their late bidding behavior. They need to weigh the attractiveness of these features for late bidders on one side against their potential deterrence effects on new users on the other side (Backus et al., 2015).

In the next section, we present a theoretical background of late bidding strategies in online auctions, followed by an introduction of the concepts of mobile push notifications and potential effects on bidding behavior. Our hypotheses detail the predicted relationship between late bidding and mobile push notifications. After we present our field data approach and key variables, we outline our results, which reveal the predicted relationship between mobile push notifications and late bidders' success, together with their implications. We conclude with some limitations of this study and suggestions for further research.

4.2 Literature Review and Hypotheses

4.2.1 Last Minute Bidding Behavior

Customers of online auctions oscillate between rational decisions to maximize their utility and emotionally driven auction fever (Adam, Krämer, & Müller, 2015). Late bidding, or sniping, might help them do both. When late bidders win, they feel effective (Kamins et al., 2011), suggesting an emotional component in which the "joy of winning" is stronger than the "frustration of losing," especially in social competitions with other bidders (Adam et al., 2015).

In addition, there are rational reasons for late bidding. It can conceal private information from competitors, while allowing the sniper to gather information from others' bids, about both common and private value (rare) products, until the last moment (Bajari & Hortaçsu, 2003; Ockenfels & Roth, 2006; Roth & Ockenfels, 2002). With regard to common value products, all bidders likely assume the same

value, but each bidder also issues private signals (Cheema et al., 2012). Late bidders can include competitors' valuations of the focal item in their own decisions. Furthermore, the last minute bid leaves competitors no chance to respond before the end of the auction. Thus this strategy is especially effective in competitions with naïve, incremental bidders—who might not be familiar with the second-price auction format and confuse it with first-price English auctions (Ockenfels & Roth, 2006). These incremental bidders approach their actual willingness to pay by bidding in small steps, just over the current high price. If we assume the naïve incremental bidder and the sophisticated sniper have the same willingness to pay, the latter will win with its late bid, because the former has no time to respond (Wenyan & Bolivar, 2008). Other benefits accrue because late bidders can avoid a "bidding war," which may keep the price lower (Roth & Ockenfels, 2002), and use sniping as a counter-strategy against shilling (i.e., the practice in which sellers illegally try to boost the current high price by bidding themselves or letting friends bid; Barbaro & Bracht, 2006).

Although customers often can sort their search results on auction platforms by the soonest ending auctions, such that they occasionally bid quite late, Wenyan and Bolivar (2008) distinguish these bidders from deliberate snipers who actively seek to win an auction with one "fatal strike." Similarly, the "opportunists" in Bapna et al. (2004) classification are not snipers; they just try to make the best bargain at the end of an auction.

We thus regard late bidding as a prevalent strategy, despite auction providers' efforts to advise users to adopt proxy bidding systems. In these systems, auction platforms identify submitted willingness to pay values as a hidden reservation price. A proxy bidding agent responds automatically and stepwise to competing bids, until the value reaches this maximum reservation price. If outbid, the platform notifies the bidder, and the bidder can revise the reservation price (Bajari & Hortaçsu, 2003; Feng, Fay, & Sivakumar, 2016).[5] But auction platforms simultaneously promote late bidding

[5] In the auction platform we study, the mobile app users also receive notices of being outbid as push notifications. However, using the proxy bidding agent does not correspond with a late bidding strategy, so we exclude these push notifications from the present study.

behavior—or at least "auction fever"—by highlighting the time remaining as it winds down (Adam et al., 2015).

Finally, a pertinent risk of a late bidding strategy is missing the deadline (Roth & Ockenfels, 2002), such as if the bidder lacks access to a computer or gets distracted from monitoring the auction. Still, snipers appear to remain convinced about their strategy, even if their late bid comes in under the required minimum price and thus is not successful; late bidders do not attribute this type of failure to their approach (Brint, 2003; Kamins et al., 2011). Empirical evidence also confirms this attitude, because snipers achieve more efficient winning rates than early bidders (Wenyan & Bolivar, 2008; Yang & Kahng, 2006). Accordingly, late bidding strategists likely seek to overcome the risk of unavailability, as well as the effort needed to monitor auction deadlines (Kamins et al., 2011). We investigate how mobile push notifications, as real-time reminders, and mobile access to online auctions might address these challenges.

4.2.2 Mobile Push Notifications in Online Auctions

Mobile devices provide perceived ubiquity in terms of continuity, immediacy, portability, and searchability (Okazaki & Mendez, 2013), and they enable customers to participate in commerce activities anywhere and anytime, such that through "communication-in-motion," they can react immediately to time-critical issues (Balasubramanian et al., 2002). On the other side, mobile targeting enables marketers to reach customers according to geographical and temporal segmentations and targeting, which likely enhances their ability to influence the purchase behavior of consumers with mobile devices (Luo, Andrews, et al., 2014).

Mobile devices have always been intrusive, such as when incoming calls or messages interrupt users engaging in other tasks. But the myriads of mobile applications available today also send variously relevant, time-sensitive, and location-aware messages to users' mobile devices (Warren et al., 2014); if they respond, users usually are redirected to the content specific to that app, such as an auction, and can act instantaneously, such as by bidding before the auction ends.

From an interactive marketing perspective, mobile push notifications are hybrid entries in the push–pull marketing spectrum (Bacile et al., 2014; Unni & Harmon,

2007; Xu, Teo, Tan, & Agarwal, 2009), oscillating between pushing direct marketing and pulling co-produced services. That is, mobile push notifications require customers to initiate the download and installation of the mobile app, as well as register for the specific service, such that the process begins with a pull action by presumably involved customers. Usually, both the mobile app and the mobile operating system ask for permissions and specific configurations for the push notification. Rather than take advantage of this hybridity though, marketers often simply seed firm-initiated marketing messages, a strategy labeled "pull with firm production" (Bacile et al., 2014). In contrast, "pull with co-production" could be a foundation for a conceptual shift from "marketing communication sent to personal media as an attention-getting promotion disconnected from direct consumer participation to a service-like, participatory offering" (Bacile et al., 2014, p. 127).

In online auctions, the service-like characteristics of push notifications are evident, because the platform provider facilitates mobile access and offers reminder and notification services to customers. Registered auction platform users who have installed the related mobile application declare their interest in specific auctions by adding items to their watch lists. This interactive feature reduces effort during the purchase decision process, because it temporarily stores items of interest to customers, so that they can easily view them again (Close & Kukar-Kinney, 2010). The mobile app we study sends push notifications about watched items at a customized time (by default, 15 minutes) before the auction's deadline. The customer must be engaged to even create the watch list, so these reminder push notifications are co-produced in the best sense. This act of self-targeting should increase the relevance of push notifications. Furthermore, as Bacile et al. (2014) suggest, the notifications can act as risk reduction mechanisms that influence purchase activity, so we predict they affect bidding behavior near the end of an auction.

4.2.3 Do Mobile Push Notifications Facilitate a Late Bidding Strategy?

Mobile push notifications, reminding users that an auction is ending, exist only after customers have found a specific item and added it to their watch list. The action of creating the watch list offers an indication of product involvement and purchase intentions (Close & Kukar-Kinney, 2010) and also provides a tool to monitor, observe, and learn over the course of the auction. Using a watch list option

constitutes an expression of bid intention per se, without displaying the bidder's valuation of the item of interest—a behavior typically adopted by late bidders (Roth & Ockenfels, 2002). Therefore, we anticipate that snipers use the watch list feature more frequently to organize their bidding behavior, which means that they also receive push notifications about the end of the focal auction.

Push notifications come through the mobile app, meaning that users can react anywhere and anytime (Shankar et al., 2010). If the user intends to snipe in an auction, the ability to react instantaneously may provide an advantage over competing users. Furthermore, due to the co-producing and self-targeting character of push notifications, these messages confront consumers with reminders about not just the expiring auction but also their initial buying interest. By customizing the communication they receive through their mobile devices, consumers likely reduce their perceptions of the risk of negative outcomes related to the messages or the related purchase decisions (Bacile et al., 2014). Consequently, prospective bidders should be more persuaded and strive to win the auction. Prior literature (Roth & Ockenfels, 2002; Wenyan & Bolivar, 2008) already identifies the advantage to late bidders, because they bid so close to the end that no competitors can respond. In turn, we predict that simply because users receive the reminder push notification in the last minutes of an auction, they can bid late more effectively and increase their probability of sniping and winning an auction, compared with users who neither receive a reminder nor are online. That is, late bidders use tools that support their bidding decisions and efficiency (Bapna et al., 2004; Häubl & Trifts, 2000). Both watch lists and mobile push notifications should produce distinctive advantages, so we also predict that among the group of late bidders, successful winners are more likely to have applied these features. We hypothesize:

H1a: Late bidders are more likely to use the watch list feature than bidders with other bidding patterns.

H1b: Among watch list users, late bidders are more likely to use mobile push notifications than bidders with other bidding patterns.

H2a: Among late bidders, users of the watch list feature are more likely to win the auction than non-watch list users.

H2b: Among late bidders using the watch list feature, users of mobile push notifications are more likely to win the auction than non-push notification users.

Late bidders represent various groups, including not just strategic snipers (Wenyan & Bolivar, 2008) but also last-minute opportunists (Bapna et al., 2004), who seek the advantages associated with using mobile push notifications as reminders. In common value auctions for example, bidders bid strategically to avoid the winner's curse (i.e., feeling that they paid too much) and try to realize a surplus, and such outcomes are more likely for experienced users (Bapna, Jank, & Shmueli, 2008). Experienced users also are less likely to overbid their price valuation (Feng et al., 2016), and most deliberate late bidders are experienced and sophisticated (Roth & Ockenfels, 2002; Wenyan & Bolivar, 2008). Therefore, within the group of late bidders, consumers who receive mobile push notifications enjoy a decisive advantage, due to the supportive tool that monitors the course of an auction and offers signals about their competitors (Bajari & Hortaçsu, 2003). Therefore, we hypothesize:

H3: Among late bidders using the watch list feature, the usage of mobile push notifications increases their chances of winning an auction.

Table 6 summarizes the hypothesized relationships between late bidding, watch list and push notification usage as well as success chances.

Table 6.

Summary of Hypothesized Relationships (Study 3)

Main effects			
H	*Independent variable*	*Dependent variable*	*Expected effect*
1a	Late bidding	Watch list usage	Positive
1b	Late bidding	Push usage	Positive
2a	Successful late bidding	Watch list usage	Positive
2b	Successful late bidding	Push usage	Positive
3	Push usage	Success rate	Positive

4.3 Data Set and Methodology

4.3.1 Data Collection

We analyzed field data from the German marketplace of an online auction platform with a sealed-bid, second-price auction format and hard closes. The database contains detailed behavioral and transactional information at the customer and item levels, related to specific auctions held during June–August 2014. We include all auctions that started or ended in this period, and we excluded those that started before the period, ended after it, or were interrupted for any reasons during the period. Participants could bid on the auction website or corresponding mobile application. The surrounding conditions remained stable during this period, such that there were no new mobile app releases or designs, nor were there any changes to the general terms and conditions. The items on the platform are manifold and rarely comparable, though some standard products can be identified by a distinct product code in the platform's product catalog. To reduce the extensive product variability and selection effects related to product characteristics (Backus et al., 2015), we focused on the top 330 most listed and classifiable products auctioned during the observation period.

Because we seek to measure late bidding success rates, we excluded fixed price offerings or transactions in which prospective buyers simply name their own price. Registered, logged-in users interested in certain auctioned items can bookmark them using individual watch lists; each item on the watch list triggers an e-mail reminder several hours before the end of its auction for website users. Mobile app users instead receive a mobile push notification at a predefined time of 15 minutes, or some other customized time, before the end of a watched auction. The median time set by users in our initial data set was 15.2 minutes. We exclude all other mobile push notifications related to a bid, most of which refer to an outbid and thus are not relevant to snipers who bid just once and at the last moment. Accordingly, our analysis focuses specifically on purely reminder notifications. We link the submitted bids to mobile push notifications if users bid temporally after the timestamp of the push notification, even if the bid is submitted on a computer instead of the mobile device. This realistic scenario acknowledges that mobile push notifications attract the

attention of users who might already be working or browsing on a personal computer.

At the auction level, the initial sample included 83,182 offered items, 61,614 (74.1%) of which sold successfully in contests with 1,001,668 bids. Of all these bids, 10.6% were submitted in the last minute, and the fraction of winning bids in this minute was 55.3%. Snipers are defined as bidders who submit their one and only bid in the last minute in an auction with at least one more competitor. These snipers participated in 56.8% of all sold auctions and won 41.2% of these auctions. Accordingly, we identify 60,670 late bidding attempts in the sample, 41.8% of which were successful. To investigate the impact of mobile push notifications, we also consider the prior use of a watch list, because using a watch list affects the chances of receiving a mobile push notification and offers a proxy for purchase intentions. To reduce any bias related to bidders' intentions to bid, we focus on the success rate for a comparable group of last-minute bidders. A key subsample thus consists of the 30,686 late bidders who also used the watch list. Table 7 shows an overview detailed by product category.

Table 7.

Sample Overview: Top 330 Auctioned Products, by Categories (Study 3)

Category	Number of products	Number of auctions	Conversion rate [%]	All bids in last minute [%]	All winning bids in last minute [%]	Auctions with sniping attempts [%]	Auctions won by sniping [%]
Books	9	989	74.7	7.5	24.9	25.6	20.0
Cell Phones & Accessories	158	43,990	75.7	10.6	60.7	62.8	45.3
Computer, Tablets & Networking	60	14,097	79.1	10.8	53.0	56.6	41.2
DVDs & Movies	18	2,433	78.4	5.9	26.5	27.0	22.2
Household Supplies & Cleaning	2	574	52.1	11.1	59.5	57.2	43.5
Video Games & Consoles	83	21,099	67.3	10.7	49.8	48.5	35.1
Total	330	83,182	74.1	10.6	55.3	56.8	41.2

4.3.2 Measures

To determine a last minute bidder's *success* in winning an auction, we used a binary variable (won = 1, else = 0). In another binary variable, we coded customers who received a mobile *push* notification before their bid as 1, and all others as 0. Bidders could bid immediately on their mobile device but did not have to, such that they also could switch to the browser version of the auction platform for various reasons. Therefore, we also measured whether they used their *mobile* device to make their bid (mobile bid = 1, non-mobile bid = 0).

Late bidders' characteristics. Previous research shows that bidders' experience is a predictor of late bidding behavior (Roth & Ockenfels, 2002). We therefore include variables to control for this effect. For the measure of *total experience*, we calculate the total number of items purchased on the auction platform in the year before our observation period. We also differentiate *category experience* (Feng et al., 2016) and measure bidding experience in the category represented by the focal auction, according to the total number of bids in the corresponding category. This number is only available for the observation period.

Bid-specific characteristics. By comparing each unique bid value against the expected price, operationalized as the average final price of the specific product in the observation period, we gain a proxy for the *seriousness* of each bid (Backus et al., 2015). The higher this ratio is, the greater the bidder's willingness to win (and pay). Snipers who submit their bids closer to the end of the auction reduce the time that competitors (including other snipers) have available to react, so we also measure *remaining time* as the difference between the bidding timestamp and the auction's close, in seconds.

Auction-specific characteristics. Previous literature shows that bidding competition influences late bidding behavior (Kamins et al., 2011) and can drive auction fever (Adam et al., 2015) and overbidding (Feng et al., 2016). Therefore, we control for the *number of bidders* in an auction (Wood, Alford, Jackson, & Gilley, 2005). A recent study also shows that in periods with less general activity, the density of snipers increases (Backus et al., 2015). In popular time slots, all types of bidders are online and likely to participate in the last minutes of an auction. Accordingly, the

ending times of auctions often correspond with these prime times (i.e., evenings and weekends), when peer-to-peer sellers also often start their auctions, which then run for 1 to 10 days. We define *prime time* as 4:00–9:00 p.m. (CET), when 56.4% of all auctions in our initial sample end (prime time = 1, else = 0). On *weekends* (Saturday and Sunday = 1, else = 0), 46.3% of these auctions end. The auction platform we study also differentiates consumer-to-consumer (C2C) from professional business-to-consumer (B2C) sellers, and the *seller* type might affect a bidder's willingness to win. In our initial sample, 92.8% of the auctions were offered by C2C sellers (C2C = 1, else = 0).

Finally, by including *category-specific fixed* effects, we seek to account for the potential effects of different product categories. We created six category dummies (cf. the categories in Table 7; the specific category = 1, else = 0). To control for positive skew and diminish the influence of extreme values, we log transformed the total, category, and mobile experience variables, as well as seriousness, after adding 1 to any variables that can take a 0 value.

Multicollinearity should not be a threat, because (1) none of the variables correlated very highly (maximum = .49), (2) the average tolerance value was greater than .10 (M = .89; minimum = .74), and (3) the maximum variance inflation factor was well below the threshold of 10.0 (M = 1.14; maximum = 1.35) (Hair et al., 2013). Table 8 provides the descriptive statistics of the variables.

Table 8.

Correlation Matrix and Descriptive Statistics (Study 3)

		1	2	3	4	5	6	7	8	9	10	11
Success	1	1										
Push notification	2	.04***	1									
Mobile device	3	-.05***	.49***	1								
Total experience	4	.04***	-.04***	-.11***	1							
Category experience	5	-.11***	-.06***	-.06***	.36***	1						
Seriousness	6	.18***	-.05***	-.04***	-.11***	-.24***	1					
Remaining time	7	-.14***	.02***	.03***	-.07***	-.00	.19***	1				
Number of bidders	8	-.14***	.01*	.16***	-.14***	-.04***	-.00	.03***	1			
Prime time	9	-.03***	-.01	.00	.02***	.05***	-.01	.02**	-.01	1		
Weekend	10	-.03***	-.01	.00	.02*	.03***	-.03***	-.03***	-.00	.04***	1	
Seller	11	.01*	.02***	.03***	-.05***	-.13***	.06***	-.06***	.03***	.07***	.12***	1
N		30,686	28,172	30,686	27,749	30,686	30,686	30,686	30,686	30,686	30,686	30,686
Mean		.44	.51	.40	3.67	1.33	-.05	2.28	10.18	.64	.52	.90
SD		.50	.50	.49	1.33	.88	.42	.44	10.97	.48	.50	.31
Min		0	0	0	.69	.69	-5.19	.69	0	0	0	0
Max		1	1	1	8.32	5.73	6.94	3.40	60	1	1	1

* $p < .05$. ** $p < .01$. *** $p < .001$.

4.3.3 Specification

The test for differences between the distribution of late bidders, according to their watch list and mobile notification usage, relied on Pearson's chi-square test, which can analyze categorical data appropriately. To model the probability of late bidding success, we use a logistic regression to identify the odds ratio of the independent variables. The model is specified as:

$$\begin{aligned}&\text{success}_{ijkl} = \\ &b_0 + b_1(\text{push notification}_{ij}) + b_2(\text{mobile device}_{ijk}) + b_3(\text{total experience}_j) \\ &+ b_4(\text{category experience}_j) + b_5(\text{seriousness}_{jk}) + b_6(\text{remaining time}_{ik}) \\ &+ b_7(\text{number of bidders}_i) + b_8(\text{prime time}_i) \\ &+ b_9(\text{weekend}_i) + b_{10}(\text{seller}_i) + \mu_{ij} + \alpha_l + \varepsilon_{ijkl},\end{aligned}$$

where i refers to the auction of an unique item; j indicates the late bidder; k is the specific bidding submission; l is the category; μ_{ij} captures auction- and bidder-specific effects (Feng et al., 2016); α_l represents category dummies; and ε_{ijkl} is the error term. Because we also seek to investigate the influence of the explanatory variables on success rates and whether they depend on mobile push notifications, we include all interaction terms with push notification and the corresponding controls (i.e., mobile device, total experience, category experience, seriousness, remaining time, number of bidders, prime time, weekend, and seller) in an additional model.

We account for product selection bias in our subsample of frequently auctioned items (and include category effects), as well as the potential bias that might arise because late bidders use all the same feature (watch list). There also might be endogeneity issues with the variables of total experience, category experience, and number of bidders, due to unobservable reasons (Feng et al., 2016). Therefore, we adopt an instrumental variable approach from Feng et al. (2016), who argue that group averages are appropriate instruments to overcome endogeneity in the experience variables, because they are unlikely to relate endogenously to an individual sniper's late bidding performance. We also could identify the start price of an auction as a good predictor of number of bidders in an auction (Wood et al., 2005). Thus, we use

this figure as a feasible instrumental variable (instead of the auction's runtime, cf. Feng et al., 2016) which does not relate to the late bidding outcome.

With a two-step procedure (Bascle, 2008; Feng et al., 2016), we first predicted the fitted values for the three focal variables by regressing each endogenous variable on the corresponding instrument variable (i.e., average total experience of all late bidders in one auction, average category experience of all late bidders in one auction, and the start price of the focal auction) and on the remaining exogenous variables. Then in the second step, we replaced these three original values with the created fitted values in the regression.

4.4 Results

In 50.6% of all last minute bidding cases, the customer used the watch list to bookmark the corresponding auction; in other bids, only 29.6% of users adopted this feature. On the flipside, 18.0% of bidders using the watch list for a certain auction submitted a late bid, whereas customers who did not watch an auction only bid in the last minute in 8.2% of the cases (Table 9). The odds ratio thus indicate that the odds of bidders' watch list usage were 2.44 times greater for late bidding strategists than non-snipers ($\chi^2(1) = 10{,}940$, $p < .0001$). In support of H1a, late bidders use the watch list feature more than their non-sniping competitors.

Table 9.

Watch List Usage of Late Bidders vs. Non-Late Bidders (Study 3)

	Watch list usage		
Row percentage *Column percentage*	No	Yes	*Total number*
Non-late bidders	70.45 91.76	29.55 82.03	474,066
Late bidders	49.42 8.24	50.58 17.97	60,670
Total number	363,956	170,780	534,736

Note. $\chi^2(1) = 10{,}940$, $p < .0001$.

Among watch list users, 51.4% of all sniping attempts followed a mobile push notification. Among all other bidder types, in only 10.3% of the auctions did the bidder receive a mobile push notification. Again taking another perspective, 62.0% of all receivers of mobile push notifications submitted their single bid in the last minute of the auction. If no push notification is involved, an auction features just 15.1% snipers among all its bidders, and the rest follow a different strategy (Table 10). This odds ratio shows that the odds that bidders use the mobile push notification were 8.86 times higher for snipers than for non-snipers ($\chi^2(1) = 21{,}904$, $p < .0001$). Thus, we have evidence in support of H1b, and late bidders are more likely to use mobile push notifications than are other bidders.

Table 10.

Mobile Push Notification Usage of Late Bidders vs. Non-Late Bidders (Study 3)

	Mobile push notification usage		
Row percentage *Column percentage*	No	Yes	*Total number*
Non-late bidders	89.66	10.34	85,849
	84.88	38.03	
Late bidders	48.65	51.35	28,172
	15.12	61.97	
Total number	90,678	23,343	114,021

Note. $\chi^2(1) = 21{,}904$, $p < .0001$. The difference between total watch list usage in Table 9 and the total number in this table results from the missing values for push notification usage. That is, we excluded ambiguous push notifications, such as those that interacted with notifications of outbids or when customers bid *before* a push notification. Non-late bidders tend to make these prior bids, so their fraction of actual push notification usage is underestimated.

We focus on just the late bidders in our sample to investigate the different distributions of watch list and mobile push notification usage between auction winners and losers. Among successful late bidders, 53.2% have used the watch list, and 47.9% of the watch list–using late bidders won the specific auction, compared with 39.6% successful late bidders who did not use the watch list (Table 11). The odds that late bidders used the watch list were 1.41 times higher for successful than for unsuccessful bidders ($\chi^2(1) = 413$, $p < .0001$).

Table 11.

Watch List Usage of Late Bidding Winners vs. Late Bidding Non-Winners (Study 3)

Watch list usage			
Row percentage *Column percentage*	No	Yes	*Total number*
Late bidding non-winners	55.27 60.43	44.73 52.06	32,787
Late bidding winners	46.77 39.57	53.23 47.94	25,369
Total number	29,984	28,172	58,156

Note. $\chi^2(1) = 413$, $p < .0001$.

Then, among the subsample of watch list users, mobile push notifications were received by 53.7% of successful late bidders. Late bidders who received push notifications won 50.1% of their auctions; those who did not receive push notifications won in 45.7% of the cases (Table 12). The odds ratio shows that late bidders' use of mobile push notifications was 1.19 times more likely for winning than for non-winning bidders ($\chi^2(1) = 55.0$, $p < .0001$). Hence, we find statistical support for H2a and H2b.

Table 12.

Mobile Push Notification Usage of Late Bidding Winners vs. Late Bidding Non-Winners (Study 3)

Mobile push notification usage			
Row percentage *Column percentage*	No	Yes	*Total number*
Late bidding non-winners	50.77 54.33	49.23 49.91	14,667
Late bidding winners	46.35 45.67	53.65 50.09	13,505
Total number	13,707	14,465	28,172

Note. $\chi^2(1) = 55.0$, $p < .0001$.

Table 13.

Results of the Logistic Regression on Successful Late Bidding Attempt (Study 3)

	Model 1		Model 2		Model 3		Model 4	
	Coeff. *(SE)*	Odd ratio	Coeff. *(SE)*	Odd ratio	Coeff. *(SE)*	Odd ratio	Coeff. *(SE)*	Odd ratio
Intercept	1.958*** (0.108)	7.084	1.688*** (0.145)	5.409	-0.176 (0.231)	0.838	0.228 (0.335)	1.256
Push notification (push = 1)	0.251*** (0.030)	1.286	0.889*** (0.201)	2.433	0.243*** (0.029)	1.275	-0.400 (0.454)	0.673
Mobile device (mobile = 1)	-0.023 (0.032)	0.977	-0.045 (0.057)	0.956	-0.057 (0.030)	0.945	-0.083 (0.055)	0.920
Total experience[a] (log)	0.114*** (0.011)	1.121	0.127*** (0.015)	1.136	0.082*** (0.012)	1.085	0.078*** (0.017)	1.081
Category experience[a] (log)	-0.244*** (0.018)	0.784	-0.196*** (0.023)	0.822	-0.212*** (0.019)	0.809	-0.148*** (0.026)	0.862
Seriousness (log)	1.067*** (0.037)	2.907	1.189*** (0.056)	3.285	0.845*** (0.040)	2.329	1.017*** (0.059)	2.764
Remaining time (in sec)	-0.193*** (0.001)	0.981	-0.029*** (0.002)	0.972	-0.030*** (0.001)	0.979	-0.032*** (0.002)	0.969
Number of bidders[a] (log)	-0.769*** (0.034)	0.464	-0.719*** (0.046)	0.487	0.241** (0.092)	1.273	0.031 (0.135)	1.031
Prime time (4 to 9 P.M. = 1)	-0.129*** (0.028)	0.879	-0.097** (0.040)	0.908	-0.138*** (0.027)	0.871	-0.101** (0.039)	0.904
Weekend (Sat./Sun. = 1)	-0.119*** (0.027)	0.888	-0.150*** (0.039)	0.861	-0.097*** (0.026)	0.908	-0.131*** (0.037)	0.877
Seller (C2C = 1)	-0.082 (0.048)	0.922	0.056 (0.068)	1.058	0.042 (0.045)	1.042	0.139* (0.064)	1.150

(continued)

(continued)

	Model 1		Model 2		Model 3		Model 4	
	Coeff. *(SE)*	Odd ratio	Coeff. *(SE)*	Odd ratio	Coeff. *(SE)*	Odd ratio	Coeff. *(SE)*	Odd ratio
Push × Mobile			0.005 (0.069)	1.005			0.013 (0.066)	1.013
Push × Total experience[a]			-0.045* (0.022)	0.956			-0.005 (0.025)	0.995
Push × Category experience[a]			-0.129*** (0.035)	0.879			-0.141*** (0.038)	0.869
Push × Seriousness			-0.242** (0.075)	0.785			-0.322*** (0.080)	0.724
Push × Remaining time			0.018*** (0.003)	1.018			0.021*** (0.003)	1.021
Push × Number of bidders			-0.091 (0.063)	0.913			0.376* (0.184)	1.457
Push × Prime time			-0.064 (0.055)	0.938			-0.072 (0.053)	0.931
Push × Weekend			0.058 (0.053)	1.060			0.066 (0.051)	1.068
Push × Seller			-0.282** (0.096)	0.755			-0.210* (0.090)	0.814
Category fixed effects	Included		Included		Included		Included	
Model summary statistics								
N	25,466		25,466		27,045		27,045	
Likelihood-Ratio	$\chi^2(15) = 2{,}208$***		$\chi^2(24) = 2{,}302$***		$\chi^2(15) = 1{,}653$***		$\chi^2(24) = 1{,}760$***	
c-Statistic	0.667		0.670		0.643		0.648	
R^2 (Nagelkerke)	0.111		0.115		0.079		0.084	

[a] In Models 3 and 4, the values of *total experience*, *category experience*, and *number of bidders* are replaced with fitted values.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 13 contains the results of the logistic regression models for the *success* binary outcome variable. Model 1 includes all variables in our specification; Model 2 adds their interaction terms, to test whether the influences of mobile push notifications interact with other explanatory variables. To address the previously described endogeneity issues, we replaced the total experience, category experience, and number of bidders variables with fitted values in the parallel Models 3 and 4.

In the main Models 1 and 3, mobile push notification has a significant, positive effect on the success of late bidding. Thus, we find statistical support for H3, because mobile push notifications relate to the higher success rates of late bidders. In terms of odds ratio, the odds of a late bidder who has received a mobile push notification winning an auction were 1.29 times (Model 1; 1.28 in Model 3) higher than those of a late bidder who did not receive such a notification. We also find significant effects for several of the control variables in Models 1 and 3. In particular, customers' total experience, category experience, and the seriousness of the bid relate significantly positively to the success probability of late bidders. In contrast, we find negative relationships for the remaining time, prime time, and weekend variables. The significant influence of the number of bids changes the direction between Models 1 and 3. However, the bidding device shows no significant effect on success.

In the models containing interactions with mobile push notifications, we find negative and significant coefficients with total experience (Model 2), category experience, seriousness, and seller (all in Models 2 and 4). For a late bidder with mobile push notifications (cf. late bidder without notifications), the odds to win the auction are lower (higher) if the above-mentioned variables increase (decrease), and therefore this bidder is less (more) likely to win the auction. The success of the auction depends positively on the interaction of push notification with remaining time. That is, a change in the push notification with increasing remaining time raises the odds of winning. The interaction of push notification with the number of bidders also changes between Models 2 and 4. Otherwise, no other variables interact significantly with push notification.

4.5 Discussion

4.5.1 Theoretical Implications

As previous literature has established (Kamins et al., 2011; Ockenfels & Roth, 2006; Roth & Ockenfels, 2002), late bidding is a predominant strategy in online auctions, for various reasons. However, two potential drawbacks with this strategy are the monitoring costs and the risk of missing deadlines. Rather than reiterating the consequences and drivers of sniping (Ockenfels & Roth, 2006), we investigate technological solutions that might enable it. Specifically, we show how auction platforms can provide interactive mobile features that diminish these drawbacks. Using mobile push notifications increases late bidding efficiency and increases the chances of winning an auction. The improvement of the success rate appears to result from the lower monitoring effort required and the reduced chances of missing the auction deadline. With these findings, we contribute to literature on effort-reducing interactive aids in online shopping contexts (Häubl & Trifts, 2000), which has not previously addressed uses of watch lists or mobile push notifications as helpful tools. Yet as we show, consumers clearly use these features, and in doing so, they gain advantages in their auction success.

We do not believe that bidders just transform into late bidders when they use these tools. Rather, late bidders appear more likely to use these focal features, which then enable them to finally win the auctions. To the ongoing discussion about mobile targeting (Luo, Andrews, et al., 2014), we contribute a notable example of self-targeting. In line with the marketing concept of a co-produced pull (Bacile et al., 2014), we show how late bidders help themselves by co-producing the push notifications and customizing the auction-related messages they receive, through their use of bookmarks on auctions of interest in their watch list and usage of the mobile app. Although most marketing messages received on personal devices are perceived as intrusive, especially when consumers lack control over the message (Dickinger & Kleijnen, 2008), co-producing personal media communication leads to substantial reductions of risk (Bacile et al., 2014). The consequences we observe in our data affirm this theory: Customers are more decisive and more likely to win an auction when they co-produce the hybrid pull/push marketing communication.

Our results offer noteworthy evidence of the need to take a multidevice perspective, because the bidding device had no significant effect on the chances of late bidding success. The interaction term of push notification and mobile bidding device also was not significant. Therefore, the effect of push notifications on late bidding success does not depend on which bidding device is used; half of the winning late bids preceded by mobile push notifications were submitted through non-mobile channels. Yet mobile push notifications require the use of the mobile app, so mobile devices still are crucial as touchpoints. This finding is in line with real-world evidence that 37% of all online retail transactions involve multiple devices, and 69% of these cross-device purchase paths begin on mobile devices and then move to desktop transactions (Criteo, 2016). Several factors might prompt such bidding behavior. For example, mobile devices might be considered feasible search and reminder devices, but to ensure the timely transaction, late bidders might prefer a faster, non-mobile device. Security concerns, clear arrangements of the products, usability preferences, or experience with unstable Internet connections might have influences as well.

In our examination of auction deadlines, we consider a time-sensitive component, whereas most mobile marketing research has focused on location-based components. Our findings affirm that mobile marketing literature should qualify the advantages associated with the temporal ubiquity of mobile devices. Late bidding success decreases in highly competitive prime times and weekends (Backus et al., 2015), whereas late bidders are more likely to succeed in less popular times. However, the non-significant interaction of time slots with mobile push notifications offers no statistical evidence for time-of-day related advantages for mobile push notifications. We cannot conclude that mobile push notifications generate benefits for late bidders beyond typical auction times, and consumers do not use their mobile devices to bid late more in these situations. This resistance might reflect the relatively unstable mobile connections that consumers usually experience while traveling or restrictions on their private (mobile) Internet usage during work hours. This reasoning is in line with the existing literature (Ghose & Han, 2011), such as studies that show that people use mobile devices to consume rather than generate content while traveling. In a sense, an auction transaction involves content generation, because users engage actively with the platform by placing a bid or typing in a billing address.

Finally, our finding that winning odds increase with the use of mobile push notifications remains stable, even when we control for other variables that are known to explain late bidding success. Thus, we confirm some known predictors of late bidding success. Previous research (Ockenfels & Roth, 2006; Roth & Ockenfels, 2002) shows that late bidding is a strategy of experienced bidders; we supplement this finding by showing that within the late bidder group, more experienced snipers are more likely to win. Total experience interacts negatively with mobile push notification. As it seems unlikely that push notifications lower the success probability of these experienced bidders, we reverse the argument that inexperienced late bidders profit from the use of mobile push notifications. Sophisticated late bidders might already have steady routines that do not depend on mobile push notifications, so these electronic tools offer no additional effects. In contrast, for less experienced bidders, mobile push notifications might be welcome reminders not to miss the deadline.

4.5.2 Managerial Implications

The managerial implications of our findings are threefold. First, our results supply auction platform providers with valuable insights into how consumers use interactive features like watch lists and mobile push notifications. Mobile push notifications precede bids through both mobile and non-mobile channels, so providers need to recognize and understand the multidevice interplay of auction processes on their platforms. Online auction platform providers, and online retailers in general, need a harmonized strategy across their various channels. Search results in online auction platforms should be stored on watch lists that are accessible through the mobile app too for example, still prompting notifications of deadlines.

Second, late bidders use these mobile features to improve their bidding efficiency. As Bapna et al. (2004) argue, such technologies likely appeal to participants and should increase the benefits for auctioneers. Mobile app developers therefore should integrate notifications that are customizable and useful for customers' unique purposes. In this case, the pushy push notifications actually become less intrusive and perceived as more relevant.

Third, managers of auction platforms should weight these benefits against the potential losses of new customers deterred by being sniped (Backus et al., 2015). Mobile push notifications increase the success rate of late bidders; we cannot determine whether these notifications boost late bidding behavior in general and thus the probability that new customers get sniped. Online auction managers should estimate their gains from retaining the late bidders who use such interactive tools. They also might inform new customers about the advantages of this interactive tool, because as our results show, mobile push notifications enhance the winning odds of inexperienced late bidders.

4.5.3 Limitations and Further Research

Several limitations of this study suggest avenues for further research. First, we do not establish with certainty whether a mobile push notification causally affects willingness to bid late or success. We use the temporal sequence of push notification and bid submission as a proxy, but additional survey research could ask late bidders explicitly whether they acted in response to the push notification. Experimental studies also could control for the causality of mobile push notification and the subsequent bidding strategy.

Second, we cannot characterize the true situation in which a prospective late bidder receives a mobile push notification. For example, we do not know this bidder's existing desire or perceptions of the notification. Depending on whether the notification is timely and opportune, consumers likely react differently. As Ström et al. (2014) note, we do not know enough about the situational drivers of mobile situations. Perceptions of the relevance of a mobile push notification and thus willingness and chances to win may vary with situational circumstances, based on spatial, temporal, or behavioral characteristics.

Third, regarding multidevice usage in online auction (and retail) environments, we need a better specification of the devices involved in all touchpoints over the course of the customer journey. These details are required to clarify customers' preferences and usage intentions in omnichannel retailing settings (Verhoef et al., 2015). Researchers should investigate different usage patterns across mobile and non-mobile devices to explain which steps in the consumer journey, such as searching,

bookmarking, and purchasing, take place on mobile devices and which ones are likely to prompt a change to non-mobile devices.

Fourth, we lack precise information about the reaction times of prospective customers to the mobile push notification. Such data would provide valuable insights for identifying an optimized time point, namely, when to send mobile push notifications for different customers, which would provide a form of personalization beyond the customers' opportunity to select such details. In addition to investigating reaction times to mobile push notifications, research could investigate the impact of push notifications on bidding behavior in general, not just on late bidding. It would be interesting to clarify the interplay of outbid notifications and bidding behavior at the end of an auction.

4.5.4 Conclusion

In conclusion, using real-world bidding observations, this study shows how interactive tools such as watch lists and mobile push notifications influence (late) bidding behavior. Late bidders rely on these tools to organize their bidding and make it more efficient, such that they are more successful in winning auctions with their sniping. Following mobile push notifications, non-mobile late bidding attempts succeed too, suggesting multidevice variations in the bidding course. We thus call for more studies of interactive and mobile marketing that can explain device changes during the customer journey and predict auction success factors that correspond with customers' individual situations at the moment they receive the mobile push notifications.

5 Conclusion

This dissertation comprises three independent studies, each with different approaches and separate implications. Thus it addresses three key challenges in the mobile economy for marketing research and management. Study 1 deals with *new business models* that offer their services for a significant group of consumers for a null monetary price. Studies 2 and 3 focus on mobile access to specific online platforms, as a *new marketing channel* that interacts with conventional online access. Both studies rely on field data and thus *cope with big data*. Study 2 also leverages unstructured textual data, using a linguistic approach. Beyond these field observations, this dissertation applies various methods, including qualitative expert interviews and scenario-based online experiments, to improve understanding of mobile consumer behavior.

5.1 General Implications

To identify the challenges of new business models and differentiated concepts of customer value in the digital economy, which predominantly features services offered for free, we conducted the first study. We provide a general overview of managerially relevant issues in the industry, based on our interviews with marketing executives. Study 1 provides a comprehensive overview of non-monetary customer value contributions in the free e-service industry. On the basis of both an extensive literature review and interviews conducted with industry experts, Study 1 provides several significant contributions. First, we contribute to research on free e-services (Anderson, 2009; Bryce et al., 2011; Casadesus-Masanell & Zhu, 2013) by extending existing knowledge about the dimensions and roles of WOM, co-production, and network effects in free e-services. Second, two dimensions we identified, attention and data, previously have been disregarded in customer value literature. Both values are core constituents in free e-services business models, especially those related to monetization; even beyond free industries, attention and data should be included in customer value considerations. Third, we explore the definitional boundaries of CEBs, established defined as motivationally driven behaviors (Brodie et al., 2011;

Jaakkola & Alexander, 2014; van Doorn et al., 2010). Yet paying attention and providing data are not always motivated or even conscious, so they do not qualify as CEB. Research and theory refinement opportunities thus exist, to differentiate motivational and nonmotivational customer behaviors and their impact on firms. Fourth, linking NMCVCs to business outcomes for the firm can help managers reassess the value of their customers' contributions. We note the limited applicability of revenue-based approaches of CLV (Gupta et al., 2006; Venkatesan & Kumar, 2004)—especially but not only for free e-service providers. Fifth, managers can develop their customer concept with the more nuanced view of NMCVCs. Anonymous and nonpaying users rarely have been viewed as customers, so this step is essential for establishing customer relationships with nonpaying customers.

Study 2 takes up one dimension of NMCVC by deepening the value perception of co-produced content, in the form of customer reviews (i.e., WOM for the reviewed service provider). By dealing with the question of creation and access devices, we address the impact of new digital channels on co-producing and perceiving content. This study also details a means to process unstructured field data with a linguistic approach (Erevelles et al., 2016; Malthouse et al., 2013), which can even assess textual content and style with regard to perceived helpfulness. A follow-up experiment isolates the channel perception effect; the device cue attached to co-produced content suffices to affect the appraisal.

Thus, Study 2 also makes several contributions. First, the findings provide empirical evidence of how mobile technology has changed the creation and reception of eWOM (Berger, 2014; Hennig-Thurau et al., 2010; Lurie et al., 2014). Mobile-specific linguistic characteristics make customer reviews appear less helpful to their recipients. Even just labeling a review as generated on a mobile device lowers perceptions of the degree of helpfulness among non-mobile readers. Second, this study contributes to research on source cues (Forman et al., 2008; Naylor et al., 2011) by revealing that recipients use the device tag to infer information about the reviewer. Social identity and attribution theory help explain this mechanism; recipients first evaluate their perceived compatibility with a reviewer on the basis of the device used, then attribute the motive for the review. Third, Study 2 extends research on perceived compatibility related to technology and innovation (Kleijnen et al., 2007; Meuter et al., 2005) and shows that people rely on compatibility

considerations in communications settings in which both the sender and the receiver use technologies. This insight is particularly valuable in omnichannel settings, where the borders between receivers and senders (or customers and firms) blur (Verhoef et al., 2015). Fourth, our findings related to review helpfulness (Lurie et al., 2014; Scholz & Dorner, 2013) provide a more fine-grained picture, by including two style characteristics that influence perceptions of customer reviews. Specifically, both function words and verbal immediacy increase the diagnosticity of reviews by providing additional information. Fifth, managers of user-generated platforms should recognize that content- and style-specific characteristics of mobile reviews are perceived as less helpful (cf. the same characteristics of non-mobile reviews) and therefore establish guidelines or technological solutions to improve the linguistic quality of mobile reviews (Scholz & Dorner, 2013). Sixth, online platforms should reassess their practice of tagging content with the creation device, because doing so can lead to a boomerang effect if the writing and reading devices are incongruent. Such tagging is advisable only if the platform can ensure compatibility between senders' and recipients' devices in dynamic systems.

More generally, free e-service providers should foster cross-market network effects, by constantly developing new measures to increase their attractiveness and direct the attention of non-paying customers to the offerings of their paying customers. By mining the transactional and behavioral data of an online auction provider in Study 3, we were able to analyze the effect of push notifications as a mobile-specific feature on late bidding success.

The Study 3 results highlight how two potential drawbacks of a late bidding strategy (Kamins et al., 2011; Roth & Ockenfels, 2002)—monitoring costs and risk of missing the deadline—can be reduced by interactive mobile features. Mobile push notifications increase late bidding efficiency and the chances of winning an auction. These results contribute to literature on both (late) bidding (Ockenfels & Roth, 2006) and effort-reducing interactive aids (Häubl & Trifts, 2000). Currently, the design of mobile push notifications is a remarkable example of self-targeting or co-produced personal media communication, so we can affirm: Customers are more decisive and more likely to win an auction when they perceive that they can control the messages they receive, by co-producing (Bacile et al., 2014). Mobile push notifications even affect the late bidding success, independent of the bidding device. From a

multidevice perspective (Verhoef et al., 2015), mobile messages constitute a touchpoint that affects bidding transactions on non-mobile channels. This study also centers on the deadline of auctions, a time-sensitive component, whereas most mobile marketing research has focused on location-based components (while controlling for time variables; Luo, Andrews, et al., 2014; Molitor, Reichhart, Spann, & Ghose, 2016). Although mobile devices provide temporal ubiquity, mobile users have no advantage relating to late bidding success in off-peak times when people usually work or travel. We also confirm some known predictors of late bidding success (Ockenfels & Roth, 2006; Roth & Ockenfels, 2002); more experienced snipers are more likely to win for example. Yet total experience interacts negatively with push notifications. It seems that rather inexperienced bidders benefit from this feature. Finally, online (auction) platform providers should be aware of the interaction effects across mobile and non-mobile channels and ensure that all push notifications are customizable and useful. Especially in terms of late bidding success, they should inform new customers about such features, to help them avoid being deterred by experienced snipers.

Beyond the contributions of each study, this dissertation enhances knowledge about the *online* behavior of mobile users. Most recent mobile marketing literature focuses on mobile-specific topics, such as location-based advertising with SMS coupons (Andrews, Luo, Fang, & Ghose, 2016; Bacile et al., 2014; Dickinger & Kleijnen, 2008; Luo, Andrews, et al., 2014; Luo, Reinaker, Phang, & Fang, 2014), which do not depend on genuine Internet resources. Few studies have undertaken comparisons of mobile and desktop online behavior, noting the effect and interdependence of web and mobile display ads (Ghose, Han, & Park, 2013), browsing behaviors in microblogging services and different search costs for mobile or PC users (Ghose, Goldfarb, & Han, 2013), or how online shopping behavior depends on adaptations in the mobile channel (Wang et al., 2015).

In line with these studies, this dissertation extends research on how online consumer behavior differs across mobile and non-mobile users and the mutual relationships that arise. Study 2 differentiates between mobile and non-mobile online review-generation behavior on the same online platform and also enlightens perceptions of mobile reviews on non-mobile devices. Although push notifications are a mobile-specific feature (but require access to the Internet), Study 3 examines their impact on

online auction behavior on a platform where both mobile and non-mobile customers compete. Therefore, this dissertation succeeds in showing the interplays and interrelations among mobile and non-mobile channels on online platforms.

5.2 Outlook

Several limitations of all three studies provide fruitful avenues for further research. This dissertation also produces a more general outlook for future research endeavors.

Study 1, about non-monetary customer value contribution, opens up four main research paths. First, quantitative empirical validation could reconfirm our qualitative findings and create a link between managerial perceptions of NMCVCs and performance measures for business success. Business models, company stages, and strategy goals (reach vs. growth) would be interesting moderators. A typology of free e-services related to NMCVCs, and whether they are part of a firm's core offering, could help differentiate the role and value of NMCVCs. Second, our study represents a managerial perspective on NMCVC, so it would be worthwhile to consider customers' views. Are they aware of their contribution value to free e-services? What affects their willingness to contribute NMCVCs? Third, an important issue will be to measure NMCVCs on an individual level. Only with feasible metrics can managers integrate the information into their customer equity calculations and, more generally, understand the individual value of a customer. Fourth, this study is limited to the free e-service industry, which is a suitable magnifier for important new aspects of NMCVCs. However, further research could broaden the industry setting to investigate the applicability and generalizability of our findings.

Study 2, which pertains to mobile written customer reviews and device perceptions, raises another set of potentially interesting research questions. First, this study tested the compatibility considerations of non-mobile device users only. To generalize the findings, additional research might investigate whether recipients who use mobile devices also infer compatibility correspondingly, including other mobile devices such as wearable options (e.g., smartwatches). Second, the experimental study focused on the effect of the device tag on perceived helpfulness by isolating a single review. Factors such as valence, product type, or surrounding reviews also might moderate attribution, so researchers should use these factors to investigate their

influences, following compatibility assessments or even as moderators of those compatibilities. Thus, we could learn whether source cues vary in their influence according to the specific peculiarities of any given review (environment). Third, Study 2 did not include pictures in the reviews. Not only are reviews more useful with pictures (Cheng & Ho, 2015), but mobile devices also enable consumers to take pictures during a service experience and attach them to the review. Further work could evaluate whether the rather negative text-specific characteristics of mobile reviews might be balanced out by adding pictures. Fourth, mobile behavior is very context specific, yet little is known about the situational impacts on mobile review creation intentions or output. The situational context also could influence readers' sense of compatibility, attribution, and perceptions.

In Study 3, about mobile push notification in online auctions, we identify four more research avenues. First, we cannot state with total certainty that mobile push notification causally affects (late) bidding and late bidding success, so survey research or experiments are needed to control for the causality between mobile push notifications and bidding strategy. Second, in this research context, (thus far unknown) situational circumstances can influence reactions to mobile push notifications. A prospective bidder likely reacts completely differently in stressful versus relaxed settings. Both situational drivers and causation issues are broadly important. Third, though we find that mobile notifications affect non-mobile bidding, we still need to understand the specific roles of all devices included in the course of a bidding process. It is an emerging question whether specific devices have specific functions in the general customer journey. Fourth, it would be worthwhile to include reaction times in research into mobile push notifications. Such an analysis would provide important insights about the optimized time to send push notifications to different customers.

As noted, due to the ubiquity of mobile devices, their usage underlies myriad contextual and situational conditions. Thus, there is still a need for research to learn more about the contexts in which consumers use their mobile devices and why (Ström et al., 2014). In retail environments, recent research investigates some contextual parameters. The geographical context, in terms of the physical proximity between the store and user, largely determines the effectiveness of location-based mobile advertising, such that mobile coupon responses depend on the distance

between the customer and store (or theater), as well as on the timing of that marketing measure (Luo, Andrews, et al., 2014; Molitor et al., 2016). Mobile advertising effectiveness for mobile-specific digital offerings also is influenced by the location context (i.e., whether the customer is at home or at work; Luo, Reinaker, et al., 2014), weather conditions (Li, Reinaker, Zhang, & Luo, 2015), and physical crowdedness (i.e., number of people in a subway train; Andrews et al., 2016).

In terms of NMCVCs, there is thus initial evidence of how contextual factors affect the attention of mobile users toward advertising. Further research should examine which contextual and situational determinants influence the other NMCVCs of mobile users, such as co-production, WOM, data, or network effects. For example, customer review behavior (and WOM intentions more generally) could be influenced by factors in the surroundings of the mobile user (and independent of the experienced service) that affect the user's sentiment, which in turn affect readers' perceptions of helpfulness. It also would be interesting to determine how mobile situations might alter accuracy levels. If the error rate of mobile users increases in specific situations, and if co-production quality or the decision quality in a bidding or purchase environment then decrease, intra- and cross-network effects will suffer too. The digital economy produces huge data sets, including each imaginable behavioral step on a platform, according to tracked clickstreams (Erevelles et al., 2016; Hofacker et al., 2016). Yet the availability of contextual data about mobile communications remains limited (Cumiskey & Ling, 2015).

In Studies 2 and 3, this dissertation relies on field data, reflecting subsamples of big data sets. Yet field data can only confirm associations, not causation; in these observations, subjects are not randomly assigned to treatment levels. Thus, endogeneity problems due to a (self-)selection bias or omitted variables are inherent (Hofacker et al., 2016). The answer to why somebody uses a mobile device at a specific moment, or not, is hardly observable. Nor are mobile and non-mobile consumer behavior really comparable, because the customer experience (due to design and usability features) differs, and the two channels are promoted differently. In both our quantitative empirical studies, we noted these challenges and tried to address them; in particular, we carefully sampled and matched observations. In Study 2, the data mining approach was followed up with an experiment to confirm the theory. In Study 3, we used an additional instrumental variable approach. However,

such scenario-based experiments only address internal validity by isolating the effects; they ignore the complexity of consumer behavior. Thus further research should strive to conduct controlled field experiments in cooperation with online platforms. Although such approaches are complex, both researchers and companies would benefit from accurate descriptions of the causal relationships among mobile consumer behavior, contextual settings, and final outcomes.

Appendix

Appendix 1.

Existing Literature on NMCVCs (Study 1)

Study	Dimensions of NMCVC: WOM	Co-production	Network effects	Attention	Data	Research approach	Free e-service context	Main findings on NMCVCs
Rust et al. (1995)	X					Conceptual		Return on quality: customer satisfaction leads to positive WOM, attracting new customers and leading to increased revenues
Danaher, Rust, Easton, and Sullivan (1996)	X					Empirical		Indirect benefits of service quality: improved customer perceptions result in increased attraction of new customers
Zeithaml (2000)	X					Conceptual		Economic worth of customers as a question for further research: How can WOM communication from retained customers be quantified?
Domingos and Richardson (2001)			X			Empirical		Network value of a customer: expected profit from sales to other customers who are influenced to buy
Ryals (2002)	X	X				Conceptual		Benefits of long-term relationships: process efficiency (learning and innovation), new customer acquisition (referrals and referencability), relationship benefits
Helm (2003)	X					Conceptual		Calculating the monetary referral value of customers through positive WOM
Hogan, Lemon, and Libai (2003)	X					Empirical		Value of a lost customer: influence of social effects (WOM, imitation) on future customer acquisition
Stahl, Matzler, and Hinterhuber (2003)	X	X				Conceptual		CLV needs to take into account both monetary and nonmonetary aspects: networking potential (WOM) and learning potential

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Study	Dimensions of NMCVC: WOM	Co-production	Network effects	Attention	Data	Research approach	Free e-service context	Main findings on NMCVCs
Hogan et al. (2004)	X					Empirical		WOM and advertising effectiveness: total CLV = conventional CLV + advertising ripple effect (value of customers acquired through positive WOM)
Algesheimer and von Wangenheim (2006)			X			Conceptual		Network based approach to customer equity management: including indirect effects into CE calculations
Lee et al. (2006)	X					Empirical		Incorporating WOM effects in estimating CLV: impact of WOM on CLV through cost savings for new customer acquisition
Kumar, Petersen, and Leone (2007)	X					Conceptual Empirical		Value of WOM: customer value = value from purchases (CLV) + referral value
von Wangenheim and Bayón (2007)	X					Empirical		Chain from customer satisfaction through WOM referrals to customer acquisition
Cook (2008)		X				Conceptual	X	Overview of "user contributions": taxonomy, advantages, outcomes, and motivational aspects
Gupta and Mela (2008)			X			Empirical	X	Value of nonpaying customers for an auction website taking into account direct and indirect network effects
Ryals (2008)	X	X				Conceptual Empirical		Determining the indirect value of a customer: including referrals and reference effects as well as learning and innovation
Villanueva, Yoo, and Hanssens (2008)	X					Empirical		Effect of WOM-based customer acquisition on customer equity growth
Trusov, Bucklin, and Pauwels (2009)	X					Empirical	X	Effect of WOM marketing on member growth at a social networking site
Hoyer et al. (2010)		X				Conceptual		Consumer co-creation in new product development: stimulators and impediments, impact of co-creation, and firm- and consumer-related outcomes

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Study	Dimensions of NMCVC: WOM	Co-production	Network effects	Attention	Data	Research approach	Free e-service context	Main findings on NMCVCs
Jiang (2010)	X		X			Empirical	X	Free software offers as a promotional tool: due to WOM, free offers increase a firm's total profit
Algesheimer and von Wangenheim (2006)	X	X				Conceptual		Conceptualizing CEV: CLV (= purchase behavior), customer referral value, customer influencer value, and customer knowledge value
Kumar, Petersen, et al. (2010)	X					Conceptual Empirical		Driving profitability by encouraging customer referrals: new approach to compute customer referral value (CRV) and identification of behavioral drivers of CRV
Libai et al. (2010)	X					Conceptual		Customer-to-customer interactions: dimensions and business outcomes
Stephen and Toubia (2010)			X			Empirical	X	Economic value implications of a social network between sellers in an online social commerce marketplace
Trusov et al. (2010)			X			Empirical	X	Determining influential users that have significant effects on the activities of other users in online social networks
Tucker and Zhang (2010)			X			Empirical	X	Indirect network effects in two-sided networks: sellers prefer markets with many other sellers because they attract more buyers
van Doorn et al. (2010)	X	X				Conceptual		Theoretical foundations and research directions for CEBs
Iyengar, van den Bulte, and Valente (2011)	X		X			Empirical		Opinion leadership and social contagion in new product diffusion: contagion operating over network ties within online social networks
Katona et al. (2011)	X		X			Empirical	X	Network effects and personal influences: diffusion process in an online social network given the individual connections between members
Nitzan and Libai (2011)			X			Empirical		Effects of a customer's social network on customer retention for a mobile network operator

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Study	Dimensions of NMCVC				Research approach	Free e-service context	Main findings on NMCVCs
	WOM	Co-production	Network effects	Attention Data			
Parent, Plangger, and Bal (2011)		X			Conceptual		Willingness to participate: firms can leverage participation to enact strategies that lower costs and increase prices
Schmitt, Skiera, and van den Bulte (2011)	X				Empirical		Referral programs and customer value: referred customers have a higher contribution margin and a higher retention rate
Weinberg and Berger (2011)	X		X		Conceptual		Connected customer lifetime value (CCLV): CLV + customer referral value + customer social media value
Albuquerque, Pavlidis, Chatow, Chen, and Jamal (2012)	X				Empirical	X	Value of referrals by content creators to an online platform of UGC
Gneiser, Heidemann, Klier, Landherr, and Probst (2012)			X		Empirical	X	Customer-based valuation of online social networks taking into account users' interconnectedness
Ho, Li, Park, and Shen (2012)	X				Conceptual Empirical		Customer influence value and purchase acceleration in new product diffusion: not only purchase value, but also influence value
Kraemer, Hinz, and Skiera (2012)			X		Empirical	X	Model for customer equity and the growth process of customer populations in two-sided markets
Ransbotham, Kane, and Lurie (2012)		X	X		Empirical	X	Network characteristics and the value of collaborative UGC
Zhang, Evgeniou, Padmanabhan, and Richard (2012)		X	X		Empirical	X	Content contributor management and network effects in a UGC environment: financial value of retention and acquisition of both contributors and consumers
Haenlein and Libai (2013)			X		Empirical		Network assortativity: revenue leaders generate higher-than- average value by affecting other customers with similarly high CLV

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Study	Dimensions of NMCVC					Research approach	Free e-service context	Main findings on NMCVCs
	WOM	Co-production	Network effects	Attention	Data			
Kumar, Bhaskaran, Mirchandani, and Shah (2013)	X					Conceptual Empirical		Social media return on investment and a customer's WOM value: customer influence value as link from WOM to sales
Kumar, Petersen, and Leone (2013)	X					Conceptual Empirical		Business reference value: the ability of a client's reference to influence prospects to purchase
Libai, Muller, and Peres (2013)	X		X			Empirical		Decomposing the value of WOM seeding programs in acceleration versus expansion
Vock et al. (2013)			X			Empirical	X	Entitativity and social capital impact members' willingness to pay membership fees for social network sites
Jaakkola and Alexander (2014)	X	X				Conceptual Empirical		CEB affects value co-creation by resource contributions toward the firm and other stakeholders (augmenting, co-developing, influencing, and mobilizing)
Verleye, Gemmel, and Rangarajan (2014)	X	X				Empirical		Managing CEB (cooperation, feedback, compliance, helping, and WOM) in a networked healthcare setting
Boudreau and Jeppesen (2015)		X	X			Empirical	X	Effects of platform growth on motivations of crowd complementors to co-produce
Manchanda, Packard, and Pattabhiramaiah (2015)		X	X			Conceptual Empirical		Quantifying the incremental revenues ("social dollars") for firms arising from increased customer engagement
Our study	X	X	X	X	X		X	NMCVCs in free e-services, including outcomes and managerial challenges

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