Nudges as Conversion Funnel Enhancers in Digital Business Models

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Declaration of Authorship

I hereby declare that the submitted thesis is my own work. All quotes, whether word by word or in my own words, have been marked as such.

The thesis has not been published anywhere else nor presented to any other examination board.

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Arbeit selbstständig angefertigt habe. Sämtliche aus fremden Quellen direkt und indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher weder einer anderen Prüfungsbehörde vorgelegt noch veröffentlicht.

Oliver Francis Koch

Darmstadt, March 28, 2017

Dissertation Summary

By leveraging the technological advancements in information, communication, and connectivity technologies, specifically the internet, firms continue to innovate and create value through new digital business models which are disrupting entire industries. More recent success stories include Spotify, a music streaming service which has transformed the way music is consumed and has disrupted the entire music retail industry as well as Dropbox, which has been attributed a similar disruptive role in regards to consumer file storage.

However, competition and distraction in the online space are fierce and consumers often expect products and services on the internet to be free, urging firms to rethink the design of their conversion funnel to win new customers and thus capture the value they create. The conversion funnel describes the transformation users undergo when sequentially proceeding through four stages to ultimately complete an online transaction with the firm: from being a non-visitor to becoming a visitor (also called acquisition), to becoming a registered user (also called activation) and lastly a converted customer (also called customer conversion).

While Information Systems (IS) research on the conversion funnel of digital business models has dealt quite extensively with the antecedents of consumer decision making in all parts of the funnel, big questions remain as to how firms may actively shape desired outcomes in regards to acquisitions and customer conversions. Research on acquisitions has emphasized that traditional advertising is becoming less effective due to media saturation and consumers wanting to rely on more credible sources when seeking information on new products and services. This has lead mechanisms such as referrals, which relate to passing along messages received by the marketer to one's peers, to become a critical component of marketing strategy. However, extant contributions have focused on the antecedents of consumer referral decisions, leaving a big gap as to how firms may actually enhance referrals and thus improve acquisition outcomes. Similarly, research on customer conversions has mainly focused on identifying the antecedents of consumer decision making at the neglect of shedding light on how one may actually shape conversion outcomes. On the other hand, IS research on activations is quite mature and has paid attention to both the antecedents of consumer decision making as well as how firms may drive better activation outcomes. Digital nudging, which refers to the practice of using visual user interface elements to influence consumer behavior in digital choice environments, has shown promising results in driving activation outcomes in this regard. For example, the usage of pull vs. push mechanisms in requesting information to consumers may influence their privacy concerns and thus activation outcomes. However,

digital nudges have so far been widely ignored in the context of acquisition and customer conversions.

Against this backdrop, three studies were conducted. The first study, by drawing on a randomized field experiment in the context of an online fashion service named StyleCrowd, investigates the effect of scarcity and personalization nudges in enhancing consumer referrals and thus improving acquisition outcomes. Building on this, the second study is focused on examining the potential of scarcity and social proof nudges as referral enhancers in the context of a randomized online experiment with the German startup Blinkist. Lastly, the third study examines how free trial order nudges may be used to enhance customer conversions within freemium business models by drawing on a contest-based online experiment.

Overall, this thesis expands our understanding of how digital nudges may be used to enhance acquisition and conversion outcomes within the conversion funnel of digital business models. On the acquisition end, we provide evidence of how scarcity, social proof as well as personalization nudges may increase consumers' propensity to engage in referrals and explicate the drivers that mediate these effects. Furthermore, we also shed light on the positive interaction effects between scarcity and social proof as well as the negative interaction effects between scarcity and personalization, and provide explanations for these phenomena. On the customer conversion end, we demonstrate how free trial order nudges may be used to enhance premium conversion within freemium business models. Besides unveiling the drivers that mediate this positive effect, we also explicate external factors that act as moderators. In sum, the contributions of this thesis are not limited to digital business models and digital nudges, but also extend into IS and marketing research on electronic word of mouth as well as research on cognitive biases. From a practical perspective, firms may leverage our findings for the design of their conversion funnel by carefully employing digital nudges to enhance acquisition and conversion outcomes.

Disseration Summary (German Translation)

Der Fortschritt in Informations-, Kommunikations- und Verbindungstechnologien, angetrieben durch das Internet, setzt Firmen in die Lage, durch Innovationen und neue wertschöpfende Geschäftsmodelle ganze Industrien zu revolutionieren. Zu den Erfolgsgeschichten der jüngeren Vergangenheit zählt beispielsweise Spotify, ein Musikstreaming-Service, der die Art und Weise wie Nutzer Musik konsumieren revolutioniert hat. Im Bereich Cloud-Datenspeicherung für Konsumenten hat das Unternehmen Dropbox ähnliche Veränderungen angestoßen.

Der Konkurrenzdruck im Onlinebereich ist jedoch extrem hoch und Konsumenten werden mit Werbebotschaften regelrecht überflutet. Um den generierten Mehrwert durch die Neugewinnung von Kunden abschöpfen zu können, sind Onlineunternehmen gezwungen, ihren sogenannten “Conversion Funnel” grundlegend zu überdenken und kontinuierlich zu verbessern. Der Conversion Funnel beschreibt den vierstufigen Prozess, den Nutzer bis zum Abschluss einer Online-Transaktion durchlaufen: Vom Unbekannten zum Besucher (Acquisition), vom Besucher zum registrierten Nutzer (Activation) und schließlich vom registrierten Nutzer zum konvertierten Kunden (Customer Conversion).

Während das Entscheidungskalkül von Konsumenten in allen Stufen des Conversion Funnels digitaler Geschäftsmodelle in der bisherigen Wirtschaftsinformatikforschung bereits intensiv untersucht wurde, bleiben bislang viele Fragen dahingehend offen, ob und wie Unternehmen bezüglich Acquisitions und Customer Conversions bessere Ergebnisse herbeiführen können. Frühere Forschungsarbeiten im Bereich Acquisitions zeigen, dass durch die Reizüberflutung von Konsumenten traditionelle Werbung an Bedeutung verliert und Unternehmen sich stärker auf Weiterempfehlungen (auch Referrals genannt) fokussieren sollten. Dies ist vor allem darauf zurückführen, dass Konsumenten Personen aus ihrem Netzwerk als vertrauenswürdigere Informationsquellen einstufen. Bisherige Forschungsbeiträge beschäftigen sich zwar mit dem Entscheidungskalkül des Konsumenten bei der Weiterempfehlung, lassen jedoch eine aktive Einwirkung des Unternehmens außer Acht. Analog wurden auch Conversions mit Fokus auf den Entscheidungsprozess des Konsumenten, jedoch ohne die Betrachtung von Einflussmöglichkeiten seitens des Unternehmens untersucht. Im Gegensatz dazu wurde in der Forschung zu Activations sowohl das Entscheidungskalkül des Konsumenten als auch der Aktionsradius des Unternehmens untersucht sowie Optimierungsmaßnahmen abgeleitet. In diesem Kontext haben digitale Nudges - das Nutzen virtueller Benutzeroberflächenelemente zur Beeinflussung des Konsumentenverhaltens in

digitalen Entscheidungsarchitekturen - bereits vielversprechende Ergebnisse vorweisen können. Beispielsweise konnte gezeigt werden, dass der Einsatz von pull statt push Mechanismen beim Abfragen von Konsumenteninformationen Sorgen um die Privatsphäre lindern und somit auch Registrierungsentscheidungen beeinflussen kann. Allerdings wurden digitale Nudges im Kontext von Acquisitions und Customer Conversions in der bisherigen Forschung bislang weitgehend ignoriert.

Um diese Lücke zu schließen wurden im Rahmen dieser Dissertation drei Studien durchgeführt. Die erste Studie, die auf Acquisitions fokussiert ist, untersucht den Einfluss von Verknappungs- und Personalisierungsnudges auf die Weiterempfehlungentscheidung von Konsumenten anhand eines randomisierten Feldexperiments im Kontext eines online Mode Services namens StyleCrowd. Darauf aufbauend betrachtet die zweite Studie das Potenzial von Verknappungs- und Popularitätsnudges (auch Social Proof Nudges genannt) für die Verbesserung von Weiterempfehlungen im Rahmen eines randomisierten Online-Experiments, welches in Kooperation mit dem deutschen Startup Blinkist durchgeführt wurde. Abschließend untersucht die dritte Studie wie Produktprobenudges genutzt werden können, um Customer Conversions in Freemium Geschäftsmodellen zu verbessern.

Insgesamt liefert diese Arbeit neue Erkenntnisse darüber, wie digitale Nudges zur Verbesserung von Acquisitions und Customer Conversions im Conversion Funnel digitaler Geschäftsmodelle genutzt werden können. Im Bereich Acqusitions zeigen die Ergebnisse, wie Verknappungs-, Popularitäts- und Personalisierungsnudges die Neigung des Konsumenten zur Weiterempfehlung des Produkts oder Services steigern können und welche Faktoren diese Effekte erklären. Weiterhin werden die positiven Interaktionseffekte zwischen Verknappungs- und Bekanntheitsnudges sowie die negativen Interaktionseffekte zwischen Verknappungs- und Personalisierungsnudges beleuchtet und erklärt. Im Bereich Customer Conversion zeigt die dritte Studie wie Produktprobenudges genutzt werden können, um Customer Conversion im Rahmen von Freemium Geschäftsmodellen zu steigern. Hierbei werden neben den Faktoren, die diesen positiven Effekt mediieren, auch moderierende externe Faktoren untersucht. Insgesamt sind die Beiträge dieser Arbeit nicht auf digitale Geschäftsmodelle und digitale Nudges beschränkt. Die Dissertation liefert auch Forschungsbeiträge in den Bereichen Electronic Word of Mouth und Cognitive Biases. Aus praktischer Sicht können Unternehmen die im Rahmen der Arbeit gewonnenen Erkenntnisse zur Gestaltung ihres Conversion Funnels nutzen, um durch den sinnvollen Einsatz von digitalen Nudges Acquisitions und Customer Conversions zu steigern.

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List of Abbreviations

AVE	Average Variance Extracted
CI	Confidence Interval
CV	Control variable
DV	Dependent variable
ewom	Electronic Word-of-Mouth
IS	Information Systems
M	Mean
RQ	Research question(s)
SD	Standard Deviation
SE	Standard Error
StD	Standard Deviation
Web	World Wide Web
wom	Word-of-Mouth

1 Introduction

1.1 Motivation and Research Questions

The rapid adoption of the internet on a global scale has enhanced connectivity between consumers and companies and therefore has enabled digital business models that have disrupted entire industries (Hess et al. 2016; Matt et al. 2015; Ratchford 2015). Business models are digital when "*[…] changes in digital technologies trigger fundamental changes in the way business is carried out and revenues are generated*" (Veit et al. 2014, p. 48). More recent success stories include Spotify, a music streaming service which has transformed the way music is consumed and has disrupted the entire music retail industry as well as Dropbox, which has been attributed a similar disruptive role in regards to consumer file storage (Coleman 2015; Riley 2016).

Despite the internet having opened new opportunities for digital business models to create value, competition and distraction in the online space are fierce. This urges firms to think differently about how to design their conversion funnel to win customers and thus capture the value they create (Godes and Mayzlin 2004; Porter and Golan 2006; Veit et al. 2014). The conversion funnel, often also referred to as purchase or sales funnel describes the transformation users undergo when sequentially proceeding through four stages to ultimately complete an online transaction with the firm: from being a non-visitor to becoming a visitor (also called acquisition), to becoming a registered user (also called activation) and lastly a converted customer (also called customer conversion) (Hoban and Bucklin 2015). It is the firm's objective to move as many users as possible through all stages as efficiently as possible (i.e., at minimal cost).

Information systems (IS) research on digital business models has paid a lot of attention towards topics such as the impact of new technologies on the firm's value chain (e.g., Leimeister 2012; Tafti et al. 2013), the theoretical foundations of value creation (e.g., Amit and Zott 2001; Wirtz et al. 2010), specific business models (e.g., Österle 2007; Steininger et al. 2013) as well as revenue models (e.g., Eurich et al. 2011; Teece 2010). However, there have also been noteworthy contributions across IS and marketing literature towards the conversion funnel of digital business models. Within the context of consumer activations, most research thus far has focused on the antecedents of consumer decision making. For example, Porter and Golan (2006) make the argument that traditional advertising is becoming less effective due to consumers being overwhelmed with marketing messages. They also argue that firms need to leverage referrals, which describe the process of users passing along

messages received by the marketer to their peers, for their acquisitions because consumers are increasingly relying on such credible sources when seeking to inform themselves about new products. However, despite the plethora of research on the antecedents of consumer referral decisions (e.g., Hennig-Thurau et al. 2004; Zhang et al. 2014), less is known about how firms may leverage this knowledge to shape better acquisition outcomes. In contrast, research on activations is quite mature both in terms of factors that affect consumer decision making as well as how these may be leveraged for better activation outcomes. This is owed to the fact that activation decisions are largely driven by consumer privacy concerns when revealing personally identifiable information for registering an account and privacy research being a well established research stream in IS (Li et al. 2013). Similar to research on acquisitions, customer conversion contributions have mainly focused on the antecedents of consumer decision making (e.g., Wagner et al. 2013; Wagner et al. 2014), leaving questions as to how this knowledge may be leveraged to shape better conversion outcomes. In sum, there is still a big research gap in regards to further understanding and shaping acquisition and conversion outcomes within the conversion funnel of digital business models (Veit et al. 2014).

In line with the aforementioned research gap, Weinmann et al. (2016) have called for more attention towards the potential of digital nudges in influencing consumer decision making within such digital choice environments. Digital nudging refers to the practice of using visual user interface elements to influence consumer behavior in digital choice environments (Weinmann et al. 2016). For example, displaying limited room inventory during an online hotel booking may be a nudge which generates a sense of urgency and hence influences customer conversions (Amirpur and Benlian 2015). While research on nudges has predominantly occurred in the offline world (e.g., Kahneman 2011; Tversky and Kahneman 1975), it has also expanded into IS with a focus on more traditional contexts such as IS usage, IS management or software development (Fleischmann et al. 2014). There have also been selective contributions on digital nudges within privacy research, like in the context of newsletter, website or mobile app registrations, which are directly related to activations within digital business models (Lai and Hui 2004; Li et al. 2013; Xu et al. 2009). However, to the best of our knowledge, research on digital nudges for shaping acquisitions and customer conversions remains sparse. Hence, this thesis aims to close this gap by addressing the following research questions:

RQ1: How can digital nudges be leveraged to enhance acquisitions within digital business models?

RQ2: How can digital nudges be leveraged to enhance customer conversions within digital business models?

Multiple empirical studies were conducted to address these research questions. The articles pertaining to these studies are included in this thesis and were all previously published in IS or marketing research outlets. The next section discusses the structure of the thesis in detail.

1.2 Thesis Structure and Synopses

This thesis is organized as follows. After the introduction in chapter 1, the overall research context is depicted in chapter 2, followed by the positioning of the thesis. Three studies that were published across three articles in peer-reviewed outlets were conducted to address the overall research questions. These articles, constituting chapters 3 through 5, were slightly modified for a more consistent appearance throughout the thesis (see Table 1). The first article in chapter 3 deals with the role of scarcity and personalization nudges in enhancing consumer referrals and thus improving acquisition outcomes. The second article in chapter 4 also deals with enhancing referrals but focuses on social proof and scarcity nudges. Lastly, the third study examines how free trial order nudges may be used to enhance customer conversions within freemium business models. Chapter 6 concludes the thesis with the main contributions to research and practice.

Study 1	**Chapter 3** Article 1	**Scarcity and Personalization Nudges as Referral Enhancers** Koch, O. F., and Benlian, A. (2015): *"Promotional Tactics for Online Viral Marketing Campaigns: How Scarcity and Personalization Affect Seed Stage Referrals"* In: Journal of Interactive Marketing, 32, 37-52. **VHB: B**
Study 2	**Chapter 4** Article 2	**Scarcity and Social Proof Nudges as Referral Enhancers** Koch, O. F., and Benlian, A. (2015): *"Designing Viral Promotional Campaigns: How Scarcity and Social Proof Affect Online Referrals"* In: 36th International Conference on Information Systems, Fort Worth, USA. **VHB: A**
Study 3	**Chapter 5** Article 3	**Free Trial Order Nudges as Conversion Enhancers** Koch, O. F., and Benlian, A. (2016): *"The effect of free sampling strategies on freemium conversion rates"* In: Electronic Markets, Online First. **VHB: B**

Table 1. Overview of Articles

In the following, each of the three articles with their respective publication outlets and dates are summarized and their main contributions are positioned within the context of the overall research questions. The summaries and the articles are written from the first-person plural point of view (i.e., we) in order to express that these studies were conducted with co-authors and therefore also reflect their opinions.

Article 1:
Promotional Tactics for Online Viral Marketing Campaigns: How Scarcity and Personalization Affect Seed Stage Referrals

Against the backdrop of consumers being deluged with traditional online advertising, which is increasingly manifesting in suboptimal conversion outcomes, referrals have become a pivotal channel for the acquisition strategy of digital business models. They do not only promise improved cost efficiency because consumers attribute higher credibility to messages coming from their peers and therefore are more likely to be acquired via referrals than via traditional advertising. Additionally, numerous studies have found that customers who are acquired through referrals are also more loyal and therefore more profitable. However, despite a robust understanding about the impact of referrals on acquisitions as well as of factors that drive consumer referral engagement, we know very little about how firms may actively influence consumer referral decisions. Hence, by building on extant research on referrals, which highlights the human need to reciprocate feels of gratitude as well as information value as important referral engagements drivers, and linking it to literature on cognitive biases and digital nudges, we investigate the effects of scarcity and personalization nudges on actual referral behavior. In cooperation with a German media-holding company that operates multiple e-commerce platforms, we effectively recruited 110 of their existing customers as participants for our study, a randomized field experiment within the context of a new online fashion service named StyleCrowd. Our analysis reveals that while scarcity affects referral propensity regardless of whether a campaign is personalized or not, personalization cues are particularly effective when scarcity is absent, yet are cancelled out when scarcity is prevalent. We demonstrate that consumers' perceptions of offer value drive the impact of scarcity on referral likelihood, the rationale being that consumers may believe to build more social capital when referring a scarcer offer because they perceive the value of the information they are sharing to be greater. However, our results also suggest that scarcity does need to exceed an upper threshold value to be effective. Consumer gratitude vis-à-vis the marketer on the other hand was found to be the underlying mechanism for personalization's influence on referral decisions. Personalization is a relationship marketing investment which, when perceived as an intentionally rendered benefit towards the consumer, generates feelings of gratitude. These emotions in turn stimulate consumers' need to engage in gratitude-based behaviors leading to reciprocation by complying with requests made by the marketer (i.e., in our case referrals). This study contributes to the first research question by demonstrating how digital nudges may enhance referrals and thus enable firms to improve acquisitions within digital business

models.

Article 2:
Designing Viral Promotional Campaigns: How Scarcity and Social Proof Affect Online Referrals

Building on the findings of the first study, the second article also contributes towards the first research question. It places an explicit focus on strengthening the link between research on digital nudges and referral research pertinent to information value. Thus, by drawing on prior research related to nudges and cognitive biases, we examine social proof nudges, which act as popularity signal and are attributed great potential in influencing consumers' value assessment, alongside scarcity. Our study was conducted in the context of a randomized online experiment with the German startup Blinkist, which was seeking to assess the referral effectiveness of different minimal landing pages for the global rollout of their promotional campaign. We successfully recruited 118 participants from a representative student subject pool maintained by a large public university in Germany. Our analysis substantiates the results from the first study by showing that scarcity cues affect consumers' referral propensity. Furthermore, we found that this effect is also independent of the presence of social proof nudges. However, the presence of social proof cues did lead to an amplification of scarcity's effect on consumer referral propensity. These effects can be explained via consumers' perceptions of offer value, which drive the impact of scarcity on referral likelihood and are moderated by social proof. The rationale for this is that consumers are likely to attribute great importance to social proof as it indicates the popularity of the offer. This additional information enables them to make inferences about what the offer's availability was in the past compared to now (i.e., interpretation of relative scarcity).

Article 3:
The effect of free sampling strategies on freemium conversion rates

Freemium business models, where companies offer a free basic and a value-enhanced paid version of a product, have become ubiquitous across software, games and a broad range of web services. They have emerged as one of the most popular types of digital business models, in particular because of their potential in facilitating the adoption and diffusion of new products. However, despite the many benefits of freemium, most firms suffer from low customer conversion rates and thus too few premium subscribers (3-5%), which challenges their profitability. Although there have been plenty of noteworthy contributions on the drivers of customer conversions in such business models, a big research gap remains in how firms

may actively shape user conversion decisions. Therefore, building on the theory of loss aversion, which describes a cognitive misperception that refers to the psychological anomaly that consumers perceive the disutility of giving something up to be greater than the utility associated with acquiring it, we examine the effect of free trial order nudges on consumer conversion propensity. More specifically, we analyze how two common free trial strategies influence consumers' conversion likelihood: Freefirst, where consumers start in the free and then opt into a trial of the premium version and Premiumfirst, where things are experienced in reverse order. Based on a contest-based online experiment with 225 subjects, our analysis reveals that in contrast to Freefirst, Premiumfirst significantly increases conversion propensity and that this positive effect is greater when the premium and the free version are more similar (i.e., value discrepancy is low). We put forward that this is due to high value discrepancy cancelling out the effect of loss aversion on conversion rates as it is the more dominant driver (i.e., users will go for the premium version either way because the value discrepancy is so prominent). On the other hand, when value discrepancy is low, the effect of the difference between free and premium takes a back seat so that loss aversion becomes the more dominant mechanism affecting conversion propensity. This study contributes to the second research question of the thesis by showing how digital nudges may be used to improve customer conversions within digital business models.

Besides the publications summarized above, the following articles, which are not part of this dissertation, were also published during my time as PhD candidate:

Koch, O. F. (2015): *"Business Model Development in IT Startups - the Role of Scarcity and Personalization in Generating User Feedback"*
In: 23rd European Conference on Information Systems (ECIS), Münster, Germany, **VHB: B**

Siegfried, N., Koch, O. F. and Benlian, A. (2015): *"Drivers of App Installation Likelihood– A Conjoint Analysis of Quality Signals in Mobile Ecosystems"*
In: 36th International Conference on Information Systems (ICIS), Fort Worth, USA. **VHB: A**

The next chapter aims to introduce the overall research context that is relevant to this thesis.

2 Research Context

2.1 Digital Business Models

Business models describe the logic of value creation and capture as well as the coordination of business resources (Osterwalder et al. 2005). Digital business models are characterized by the fact that they leverage technological advancements to conduct business and generate revenue differently (Veit et al. 2014). From enabling a nearly resourceless company to operate and reach potential customers on a global scale to redefining the role of the consumer in becoming a so called "prosumer" (i.e., actively contributing towards parts of the production process in the era of mass customization), advancements in information, communication, and connectivity technologies have transformed the business fundamentals of many industries (Bharadwaj et al. 2013; Burgelman and Grove 2007; Tapscott 1996).

As described in Figure 1, literature on digital business models can be categorized in terms of contributions pertinent to changes in the logic of value creation as well as those relating to value capture (Veit et al. 2014).

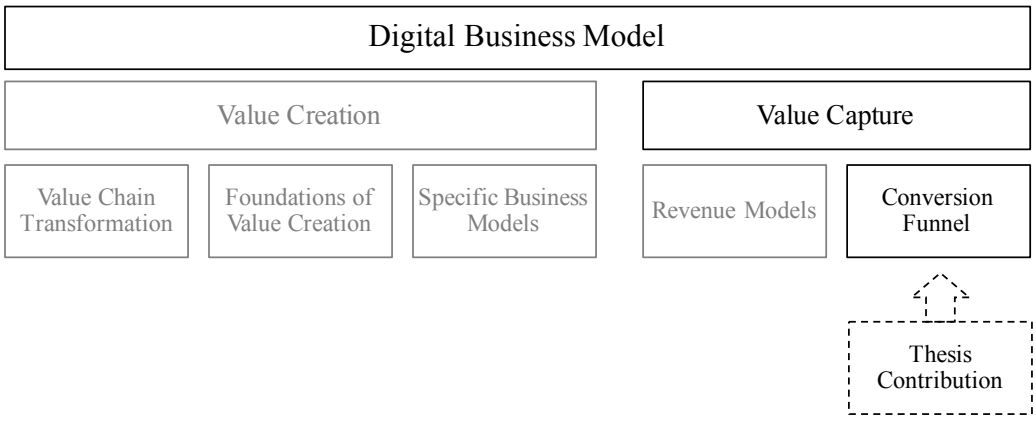

Figure 1. Digital Business Model Research and Thesis Contribution

Research on value creation within digital business models can be further described along three streams (see Figure 1). The first stream pertains to how digitilization affects the firm's value chain (e.g., Burkard et al. 2012; Leimeister 2012; Pagani 2013; Reichwald and Piller 2009; Tafti et al. 2013). Early contributions suggest that IT enables increased cross-firm boundary activities because it reduces explicit coordination costs associated with monitoring operational risk when working with other parties, in particular through enhanced information exchange and processing capabilities (Clemons et al. 1993; Gurbaxani and Whang 1991). This, in turn, has facilitated the departure from a strong bias to vertically integrate a larger part of the value creation chain. New technological advancements continue to shape discussions on how the

value chain is evolving. More recently, the focus lies on ecosystems in which both internal and external stakeholders interact on a common technological plattform to create products and services jointly (e.g., Kazman et al. 2012; Manikas and Hansen 2013), as well as the trend towards consumers becoming co-creators of companies' value propositions through models such as open innovation (e.g., Chesbrough 2006; West and Bogers 2014). In the second stream, scholars have paid attention to explicating the theoretical foundations of value creation in digital business models more broadly (e.g., Amit and Zott 2001; Sach 2013; Wirtz et al. 2010). According to Amit and Zott (2001), digital value creation comes down to four factors: efficiency, complementarities, lock-in, and novelty. Effiency because the costs per transaction may be significantly decreased, be it from economies of scale or also search cost from a consumer or supplier perspective. Furthermore, as Barua et al. (2004) suggest, a firm's informational capabilities ultimately determine the level of value creation unlocked through efficiency gains. These informational capabilitties are determined by a firm's strength in coordinating and leveraging information, processes as well as the general readiness of customers and suppliers. Conversely, complementarities generate value when customers value both a firm's and another firm's product together more than each product independently and are key to unlocking additional revenue (Brandenburger and Nalebuff 2011). Lock-ins, which prevent customers from switching to a competitors product are fundamental to digital business models that can generate value through repeat transactions (Amit and Zott 2001). Lock-ins are rooted in so-called switching costs, which do not necessarily need to be purely financial, but for example may also be experience in terms of need to learn a new product or having to migrate data from one product to another. Lastly, novelty is key to both value creation and capture as there are generally great first-mover advantages in the digital space (Lieberman and Montgomery 1988). These advantages range from creating early awareness, building switching costs and therefore creating lock-ins as well as unlocking same side network effects in some business models. Same side network effects describe situations, where the value of the good does not only depend on the value the product provides directly but also on the amount of other consumers using it, such as in the case of a messenger (Katz and Shapiro 1985). In these situations, there are usually great lock-ins that come from high switching cost which are hard to overcome, as the competing product would first need to create similar same side network effects. The last stream of research on value creation in digital business models deals with specific business models and how they use the Internet to interact and create value (e.g., Applegate and Collura 2000; Österle 2007; Steininger et al. 2013). For example Weill P (2001) highlight eight different digital models (e.g., direct

customer, full-service provider and intermediary) and discuss their success factors as well as monetization strategies.

Value capture is a big challenge for digital business models as customers expect basic services on the internet to be free and winning new customers is hard because competition for users' attention online is much more fierce than in traditional offline channels (Porter and Golan 2006; Teece 2010). Thus, research in this context of value capture contains two streams, one focused on revenue models and one related to the conversion funnel of digital business models. Research on revenue models has analyzed monetization strategies across various parts of the digital economy, ranging from digital content providers (Gallaugher et al. 2001), music (Dörr et al. 2013), online commerce (Mahadevan 2000) to games as well as cloud based platforms (Eurich et al. 2011). Overall, the suggestion is that online firms often employ multi-stream revenue models (Teece 2010). More specifically, this means that they generate revenues via multiple stakeholders in different ways, which is faciliated by the aforementioned fact that digitalization has lead companies to incorporate more stakeholders in the value creation process. For example, the music streaming service Spotify receives direct revenue from user subscriptions as well as indirect revenue via adversiting (Enders et al. 2008). Research on revenue models has also paid attention towards the effectiveness and the characeristics of different revenue streams such as usage- (e.g, Sundararajan 2004) or subscription-based (e.g., Bala and Green 2007) monetization models. Although there are many dimensions in which revenue streams may differ, they are typically characterized via two key characteristics in the digital econonomy, namely frequency and directness (e.g., Eurich et al. 2011). While directness describes whether revenue is generated directly from consumers or indirectly via other stakeholders partaking in the business model, frequency describes whether the revenue exchange occurs once (e.g., payment for a download) or via continous payments (e.g., payment for subscriptions).

As depicted in Figure 1, this thesis contributes primarily towards the second stream of research on value capture in digital business models, namely the conversion funnel. Hence, the next chapter is dedicated to this research topic.

2.2 The Conversion Funnel of Digital Business Models

The conversion funnel of digital business models is critical for capturing the value created through new products and services, as it directly relates to the firm's ability to acquire and retain customers, and thus grow (Hoban and Bucklin 2015; Teece 2010). Competition in the

online space is fierce, making it hard to acquire users' attention and move them through the funnel effectively (Porter and Golan 2006). The conversion, purchase or also sales funnel describes the transformation users undergo when sequentially proceeding through four stages to ultimately complete an online transaction with the firm (see Figure 1). While it is the firm's objective to move as many users as possible through all stages efficiently (i.e., minimal cost), some users may and do often drop off in any of the four stages. In line with Hoban and Bucklin (2015), the transformation process of the conversion funnel depicted in Figure 2 can be described as follows:

Users start as non-visitors (stage 1) which have never visited the firm's product or website and then become visitors once they have visited either of the two but without having provided personally identifiable information necessary to sign-up for an account (stage 2). The transformation process from stage 1 to stage 2 is also called acquisition. Visitors (stage 2) become registered users (stage 3) by signing up for an account, but without any money changing hands. This transformation is also referred to as activation. Lastly, registered users (stage 3) become converted customers (stage 4) by completing a transaction, whereas this transition is called customer conversion.

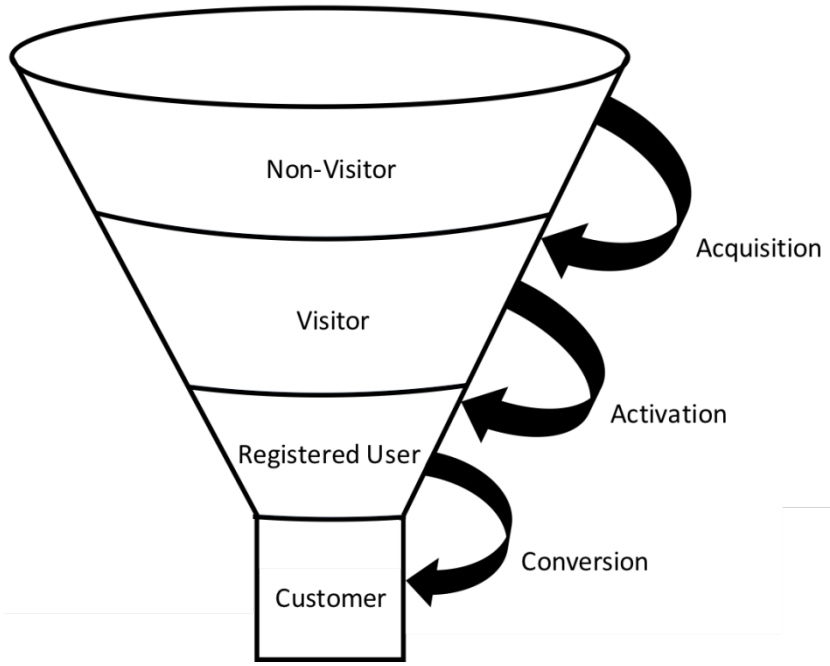

Figure 2. The Conversion Funnel of Digital Business Models

As highlighted through the literature overview in Table 2, research on the conversion funnel of digital business models can be described in terms of the antecedents of consumer decision

making as well as action/ design recommendations pertinent to each of the three transitions within the funnel (i.e., acquisition, activation and conversion) (Hoban and Bucklin 2015).

Acquisition	*Antecedents of Decision Making:* Cotte et al. (2005), Danaher and Rossiter (2011), Frambach et al. (2007), Kiang et al. (2000), McKay-Nesbitt et al. (2011), Owen and Humphrey (2009), Peterson et al. (1997), Peterson et al. (1997), Peterson and Merino (2003), Tutaj and van Reijmersdal (2012), Van Reijmersdal et al. (2009), Williams and Drolet (2005)
	Action/ Design Recommendations: no studies found
Activation	*Antecedents of Decision Making:* Belanger et al. (2002), Bélanger and Crossler (2011), Bellman et al. (2004), Benamati et al. (2016), Culnan and Bies (2003), Dinev and Hart (2004), Eastlick et al. (2006), Fogel and Nehmad (2009), Hong and Thong (2013), Li et al. (2013), Malhotra et al. (2004), Mohamed and Ahmad (2012), Pavlou (2011), Phelps et al. (2001), Sin and Chellappa (2004), Smith et al. (2011), Zlatolas et al. (2015)
	Action/ Design Recommendations: Hardt and Nath (2012), Hui et al. (2007), Martin et al. (2017), Sein et al. (2011), Xu et al. (2009)
Conversion	*Antecedents of Decision Making*: Jiang and Sarkar (2009), Dörr et al. (2013), Wagner et al. (2014), Lee et al. (2013), Bosnjak et al. (2007), Häubl and Trifts (2000), Lehdonvirta (2009), Kim and Gupta (2009), Hsin Chang and Wen Chen (2008), Tsai et al. (2011), Yoon (2002), Chen and Dubinsky (2003), Yang and Peterson (2004)
	Action/ Design Recommendations: no studies found

Table 2. Literature Overview for Conversion Funnel of Digital Business Models

Literature on the antecedents of user acquisition mainly deals with channel selection and marketing message characteristics (see Table 2). The continuous emergence of new communication channels such as Facebook, YouTube or Pinterest has lead research on acquisitions to pay a lot of attention towards channel selection (e.g., Danaher and Rossiter 2011; Kiang et al. 2000). While there is no doubt that online channels are far more efficient than traditional offline channels in exchanging information about the availability and features of a new product or service offering (Peterson et al. 1997), the relative success of a channel is dependent on continuously evolving consumer choice determinants and how channel capabilities like for example interactivity, personalization or comparison potential provide the ability to adapt (Frambach et al. 2007; Kiang et al. 2000; Owen and Humphrey 2009; Peterson and Merino 2003). However, besides extensive research on channel selection, scholars have also recognized the design and characteristics of marketing messages as factors which may influence acquisition success (e.g., Tutaj and van Reijmersdal 2012; Van Reijmersdal et al. 2009; Williams and Drolet 2005). For example, McKay-Nesbitt et al. (2011) find that negative and more emotional messages are more effective for engaging younger compared to

older people who are more responsive to rational and positive messages. More recently, and against the backdrop that consumers are being deluged with marketing messages, message credibility has become a critical success factor (Cotte et al. 2005). This has lead consumers to increasingly lean towards electronic word of mouth (ewom) when gathering information about new products, as they trust information received from their peers more than traditional advertising. (Porter and Golan 2006). Hence, a lot of attention is being paid towards referrals, which relate to passing along messages received by the marketer to one's peers and are the foundation of ewom. While there has been a lot of research on the positive effects of ewom on sales (Chevalier and Mayzlin 2006b), consumer purchase decisions (East et al. 2008), pre- and post-purchase preferences and behavior (Bickart and Schindler 2001; Gauri et al. 2008) as well as on the antecedents of consumer engagement in ewom (Hennig-Thurau et al. 2004; Zhang et al. 2014), there have been minimal contributions towards how firms may shape actually use this knowledge to shape referral behavior and hence improve acquisition outcomes. In line with this assertion, Berger (2013) has called for more research on the potential of digital nudges as referral enhancing mechanisms.

As the literature overview in Table 2 points out, research on activations is very mature and covers the antecedents of user activation as well as how firms may act on this knowledge by using digital nudges in the design of their conversion funnel to improve activation outcomes. The reason for this stream's maturity lies in it being deeply rooted in the very literature on information privacy (e.g., Bélanger and Crossler 2011; Pavlou 2011; Smith et al. 2011), because as previously eluded, providing personally identifiable information is a prerequisite to registering for an account (Li et al. 2013). Information privacy describes the extent to which consumers can control which personal information is acquired and used (Westin 1968). Concerns related to information privacy have a big impact on users' intentions to register for online products or services (Belanger et al. 2002; Sin and Chellappa 2004). Thus, from an activation perspective, it becomes critical for firms to understand and manage these privacy concerns when designing their conversion funnel. The so called privacy calculus, which suggests that consumers conduct a risk–benefit analysis whenever they are prompted to disclose information, is the most widely used framework in assessing consumer privacy concerns (Culnan and Bies 2003). However, as Bélanger and Crossler (2011) point out, there has also been research which has focused more on design and action, specifically digital nudges, to manage privacy concerns and hence improve activations. For example, Xu et al. (2009) analyze how push vs. pull information delivery nudges can be used to influence consumer privacy concerns in the context of mobile app activations. Another example is the

study conducted by Hui et al. (2007), which demonstrates how different privacy assurance nudges such as privacy seals may positively affect consumer decision making and thus bring about better activation outcomes.

Research on customer conversions has paid a lot of attention towards the antecedents of consumer decision making (e.g., Bosnjak et al. 2007; Häubl and Trifts 2000; Lehdonvirta 2009). Purchase decisions are ultimately dependent on the value that consumers perceive they are getting through a transaction. This value is a function of both the cost and the benefit a transaction may bring, whereas in online environments, cost does not only relate to the price of the good but it can come in many forms (Kim and Gupta 2009). A large stream of literature has dealt with explicating different types of costs relevant to consumer decision making in online environments, such as trust or perceived risk from uncertainty and adverse consequences of conducting transactions with a vendor (e.g., Hsin Chang and Wen Chen 2008; Tsai et al. 2011; Yoon 2002). However, research has also paid attention towards the antecedents of benefit perceptions such as ease of use or usefulness (e.g., Chen and Dubinsky 2003; Yang and Peterson 2004). More recently, research on customer conversions has gone beyond explicating generic drivers of conversion decisions by placing a bigger focus on freemium business models, where companies offer a free basic and a value-enhanced paid version of a product. Freemium business models have gained a lot of momentum in light of recent success stories such as Dropbox, Candy Crush or Spotify (Lee et al. 2013; Veit et al. 2014). Nevertheless, despite their popularity, low customer conversion rates continue to be one one the biggest challenges firms are facing when operating in freemium business models (Jiang and Sarkar 2009). Research contributions pertinent to the field have so far focused on expanding the understanding of antecedents of consumer decision making (e.g., Dörr et al. 2013; Wagner et al. 2014). For example, Wagner et al. (2014) as well as Lee et al. (2013) found that the magnitude of the value discrepancy between the premium and free version (also called premium fit) is critical to consumers decision to convert to the premium version. At the same time, they claim that if value discrepancy is too large, it hampers the benefits of free advertising, which is one reason why freemium business models are so popular in the first place. However, despite all these valuable insights, as indicated by Table 2, there have been little contributions towards how firms may actually enhance customer conversions overall, let alone in the context of freemium business models. In line with this gap, Weinmann et al. (2016) have called for research on the potential of digital nudges in influencing consumer decision making in such digital choice architectures. The following section provides an overview of literature on digital nudges.

2.3 Digital Nudges

Nudges are deliberate design decisions within choice environments which encourage or discourage the use of heuristics to influence peoples' behavior (Thaler and Sunstein). Unlike traditional economic theory that suggests human behavior is always rational, the psychological theory that nudges are built upon argues that humans may act under bounded rationality due to cognitive limitations (Simon 1955). While they may influence decision making positively or negatively, rules of thumb or so called heuristics helps humans overcome these cognitive limitations by reducing the amount of information that needs to be processed and hence the mental effort that is required (Evans 2006; Evans 2008; Tversky and Kahneman 1975). However, as Tversky and Kahneman (1975) elude, using heuristics may result in cognitive biases and systematic errors which affect the evaluation of choices and hence may result in bad decisions. Anchoring, the setting of defaults or also including incentives are commonly used nudges in the offline world (Thaler and Sunstein).

Most research on nudging has occurred in the offline context. Digital nudging, which according to Weinmann et al. (2016) refers to the practice of using visual user interface elements to influence consumer behavior in digital choice environments, is still fairly young. However, Weinmann et al. (2016) also elude to the fact that this research stream is likely to converge with design research. Hence, the differential design of user experience journeys for example, which deals with how to design and sequence parts of a user interaction for a better user experience (Cyr 2014; Lemon and Verhoef 2016), may become an additional way of influencing user decisions in digital choice environments, beyond the usage of visual user interface elements.

In line with Fleischmann et al. (2014)'s extensive literature analysis, extant IS related research falls into the following root categories of cognitive biases, which are defined as such based on their influence and decision-making process:

- *Perception biases,* which relate to the psychological tendency of losing objectivity in the perception of situations. They specifically affect the processing of newly received information. Nudges that increase transparency and contrasts between different perceptions for example may be used to reduce perception biases (Benlian 2013a; Benlian 2013b; Benlian and Haffke 2016).
- *Pattern recognition biases,* which build on the tendency that people are more likely to process information that fits into their pattern of thinking or that that relates to a topic

that is present in their minds. Availability nudges, for example, may be used to leverage that fact. (Tversky and Kahneman 1973).

- *Saliency biases*, which relate to peoples' tendency of attributing higher value to information that is more recent or salient in decision making processes. Consistency nudges, for example, may be used to leverage humans' obsessive desire to be consistent with what we have already done. This pressure causes responses in ways that justify previous decisions (Cialdini 1993b). Another example are nudges related to update frequency and magnitude in software products, which may significantly impact users' perceptions of usefulness and satisfaction, thus influencing their intention to continue using the product (Benlian 2015a; Fleischmann et al. 2016).

Furthermore, the following cognitive biases and therewith mentioned nudges are particularly relevant in the context of the studies conducted for this thesis:

- *Action-oriented biases* relate to peoples' tendency of feeling pressure to take action, which leads to premature decisions at the neglect of processing information on all possible alternatives. Scarcity nudges, which have been widely researched in the offline world, are claimed to evokes a state of physical agitation in which humans' sole focus becomes to fulfil the need in which they feel their freedom to be threatened (Cialdini 1993b). They have a positive effect on product preference, desirability, valuation and hence consumer decision-making (Van Herpen et al. 2009).
- *Stability biases* relate to the tendency of being comfortable with the status quo when there is no pressure to change, even when there may be superior alternatives. Loss aversion nudges are a prominent way of leveraging the fact that humans avoid risk, cost, and loss to a much higher degree than rewards or gain to influence consumer decision making (Kahneman et al. 1991).
- *Social biases,* which build on the tendency of striving to reach consensus and feeling the urge of complying with the expectation to conform. Social proof nudges may be used to leverage the fact that in situations of uncertainty, consumers seek behavioural guidance and hence the greater the number of people making a decision, the more an individual will perceive this to be a more valuable or correct choice (Cialdini 1993b).
- *Interest biases,* which relate to the tendency of people being motivated to obtain a favourable outcome for themselves at the expense of the organization as a whole. Personalization nudges may be used to leverage the fact that people are self-focused

and thus respond more to personalized communication as well as products and services which are tailored to their preferences (Benlian 2015b; Cox III et al. 1974).

The valuable contributions towards IS research across these cognitive biases have so far focused on more traditional research contexts such as IS usage, IS management and software development at the neglect of digital business models (Fleischmann et al. 2014). The exception to this have been selective contributions on how nudges may improve online activations, like in the context of newsletter, website or mobile app registrations (Lai and Hui 2004; Li et al. 2013; Xu et al. 2009). However, a big research gap remains regarding the potential of digital nudges for enhancing the remaining parts of the conversion funnel (i.e., acquisitions and customer conversions).

2.4 Thesis Positioning

As previously eluded, while the internet has helped create value in innovative ways, it is very challenging for digital business models to capture the value that is being created. This is especially the case because consumers are being overwhelmed with marketing messages and there being a general expectation that products on the internet should be free (Porter and Golan 2006; Veit et al. 2014). Thus, firms need to redesign their conversion funnel to successfully grow their customer base. While research on the conversion funnel of digital business models has dealt quite extensively with the antecedents of consumer decision making in all parts of the funnel, big questions remain as to how firms may actively shape activation and customer conversion outcomes (see section 2.2). This thesis responds to Veit et al. (2014)'s call for more research on how to enhance the conversion funnel of digital business models as well as Weinmann et al. (2016) urge for scholars to expand research on the potential of digital nudges in driving desired outcomes in such digital choice environments. The described problem space represents the common theme of the articles included within this thesis (see Figure 3). The contributions to the aforementioned research area lie in shedding light on the potential of digital nudges in actively enhancing acquisition and customer conversion outcomes within digital business models.

As depicted in Figure 3, the following three chapters represent each of the articles that were published in peer reviewed journals.

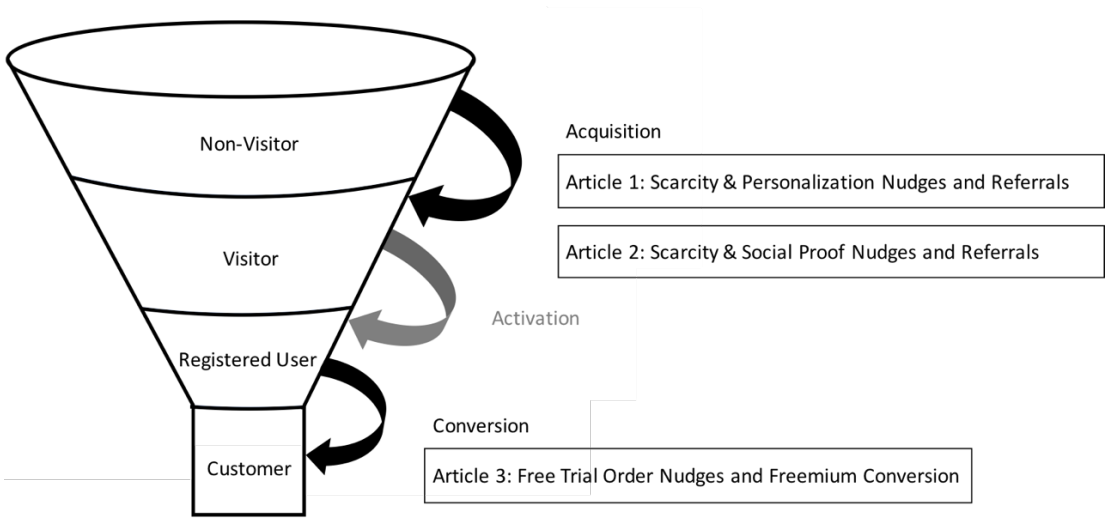

Figure 3. Parts of the Conversion Funnel Examined in the Research Articles

3 Promotional Tactics for Online Viral Marketing Campaigns

Title

Promotional Tactics for Online Viral Marketing Campaigns: How Scarcity and Personalization Affect Seed Stage Referrals[1]

Authors

Koch, Oliver Francis, Technische Universität Darmstadt, Germany

Benlian, Alexander, Technische Universität Darmstadt, Germany

Publication Outlet

Journal of Interactive Marketing, 32, 37-52.

Abstract

Against the backdrop of consumers being deluged with traditional online advertising, which is increasingly manifesting in inefficient conversion outcomes, viral marketing has become a pivotal component of marketing strategy. However, despite a robust understanding about the impact of viral marketing as well as of factors that drive consumer referral engagement, we know very little about the effect of traditional promotional tactics on consumer referral decisions. Drawing on a randomized field experiment in the context of an online fashion service named StyleCrowd, we investigate the effects of scarcity and personalization, two classical promotional cues that have become ubiquitous on the web and have received only minimal attention hitherto, on actual referral behavior. Our analysis reveals that using these cues in promotional campaigns is a balancing act: While scarcity cues affect referral propensity regardless of whether a campaign is personalized or not, personalization cues are particularly effective when scarcity is absent, yet are cancelled out when scarcity is prevalent. We demonstrate that consumers' perceptions of offer value drive the impact of scarcity on referral likelihood, while consumer gratitude vis-à-vis the marketer is the underlying mechanism for personalization's influence on referral decisions.

Keywords

Viral marketing; Word of mouth; Referral behavior; Online promotional campaigns; Scarcity; Personalization; Offer value; Consumer gratitude; Social capital; Randomized field study

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[1] This article is provided with permission from Elsevier. Original version is available at: http://dx.doi.org/10.1016/j.intmar.2015.09.005. This paper work was supported by the Dr. Werner Jackstädt Foundation grant in Germany (Grant No. 010103/56300720)

3.1 Introduction

The rapid adoption of the internet on a global scale has led companies such as Facebook, Twitter or YouTube to substantially enhance connectivity between consumers and companies by enabling social networks, social media and user-generated content (Ratchford 2015). For many firms, this has made the web to the primary advertising channel for reaching potential customers (e.g., via banner ads or social media ad campaigns), at the cost of deluging them with often irrelevant information. Hence, it is not surprising that consumers have come to perceive traditional online advertising as irrelevant and overwhelming in quantity (Porter and Golan 2006), which in turn has led them to revert to channels such as word of mouth (wom) when gathering credible information about new products.

Against this backdrop, practitioners have increased their attention towards viral marketing, which refers to the process of deliberately tapping into the power of word of mouth by "using consumer communication as a means of multiplying a brand's popularity through customers spreading the brand name of a product or name of a company." Dollarshaveclub.com, Instagram and also Pinterest, which succeeded in growing its monthly unique visitors from 40,000 to 3.2 million users in only one year, are more recent success stories that have managed to leverage viral marketing to their advantage especially in their early days (Cheney 2011; Pullen 2012).

Research on viral marketing has focused on the consequences on firm level outcomes such as sales (e.g., Chevalier and Mayzlin 2006a; Trusov et al. 2009) as well as individual level outcomes related to consumer decision-making (e.g., Bickart and Schindler 2001; Chevalier and Mayzlin 2006a; Nambisan and Baron 2007). Moreover, a comprehensive amount of literature illuminates factors that lead to participation in viral marketing campaigns (Angelis et al. 2012; De Matos and Rossi 2008; Hennig-Thurau et al. 2004) and examines content characteristics that enhance virality (Berger and Milkman 2012; Berger and Iyengar 2012; Stephen and Berger 2009a). However, though there is a robust literature on the antecedents of virality, minimal attention has been paid towards classical promotional tactics that may enhance consumer referrals. Hence, our research intends to fill this gap.

The goal and main contribution of this paper are to shed light on the potential of scarcity (i.e., the deliberate shortening of product or service availability and the communication thereof) and personalization (i.e., the endowment of a promotional campaign with personal references such as greetings), two prominent and established promotional tactics from the offline world (Arora et al. 2008; Miceli et al. 2007), in influencing consumer referral decisions and

therefore to expand our understanding of the antecedents of consumer referral behavior as suggested by King et al. (2014). We focus on these particular cues in the context of our randomized field experiment because research has demonstrated their influence on factors which are also considered particularly critical to consumer participation in viral marketing campaigns, namely product or information value as well as consumers' need to reciprocate (Frenzen and Nakamoto 1993; Pihlström and Brush 2008; Sundaram et al. 1998). Furthermore, these tactics have become popular among well established firms like Amazon.com and nascent ventures such as Mailbox, alike when generating awareness and attracting new potential customers (Nextshark 2013; Say 2013; Sharma 2013). However, despite their theoretical and practical relevance, extant contributions on viral marketing have so far neglected the role of these cues as catalysts of consumer referral behavior, thus leaving a gap in the literature that needs to be addressed.

This paper is organized as follows. In the next section, we review prior literature on viral marketing. We then draw on literature on scarcity and personalization to round up the theoretical foundation of our research model. The following section presents the hypotheses regarding the effects of scarcity, personalization and their interaction on consumer referral decisions, including the relevant mediators. The subsequent section describes the research methodology used within our experimental study, followed by our data analysis and the results of hypothesis testing. Finally, we then discuss our findings, implications and directions for further research.

3.2 Theoretical Background and Related Literature

3.2.1 Viral Marketing and Drivers of Consumer Referral Behavior

Viral marketing focuses on the diffusion of product in- formation by deliberately exploiting existing social networks to encourage people to make referrals to their friends (i.e., share news or information about a product or service) (Leskovec et al. 2007). In the context of online viral marketing particularly, referrals relate to passing along messages received by the marketer to one's peers. In essence, one can broadly describe viral marketing via two stages (Pescher et al. 2014). In the first stage, which focuses on firm created word of mouth and is often referred to as seeding, companies actively send their promotional campaigns to a targeted or untargeted audience of consumers (first stage actors). In the second stage, firms rely on peer-to-peer communications among consumers (second stage actors) for the efficient diffusion of the promotional campaign in their social networks. Referrals through first stage

actors are essential to success, because the ability to reach second stage actors is contingent on the referral decisions made by first stage actors.

Firms revert to viral marketing campaigns mainly for broad reach and cost effectiveness. Broad reach results from companies encouraging customers to spread the message among their peers. In turn, when these peers decide to become customers, they are also encouraged to spread the message among their peers, leading the company to benefit from referrals among consumers and thus triggering a viral loop (Porter and Golan 2006; Van der Lans et al. 2010). On the other hand, cost effectiveness roots from the notion that consumers attribute higher credibility to messages that come from their peers and therefore are more likely to be acquired via referrals than via traditional advertising (Godes and Mayzlin 2004). Lastly, customers who are acquired through referrals are found to be more loyal and therefore more profitable (Trusov et al. 2009).

An often cited success story of viral marketing is the online file hosting service Dropbox, which managed to implement an effective referral system that led to a surge in its customer base from 100,000 to 4 million in only 15 months. Dropbox simply encouraged referrals by offering up additional storage for customers that successfully brought on friends (Veerasamy 2014).

The emergence of social media has played an important role in making it easier and faster to implement campaigns that can go viral (Stein and Ramaseshan 2014). Companies like Facebook, Twitter or LinkedIn provide platforms that make it very simple to share information with people that reach way beyond one's immediate network. Thus, firms often implement viral marketing campaigns by building minimal landing pages on the web to convey their messages or promotional offers and then spread links to these pages over social networks to generate buzz (Ries 2011; Say 2013; Sharma 2013).

Research on viral marketing consists of two main streams. The first stream has mainly focused on its consequences such as the impact on sales, revenue or stock prices (e.g., Chevalier and Mayzlin 2006b; De Bruyn and Lilien 2008; Trusov et al. 2009). However, a substantial amount of research has also showed how it may affect individuals directly in terms of purchase decisions (East et al. 2008) as well as pre- and post-purchase preferences and behavior (Bickart and Schindler 2001; Gauri et al. 2008).

The second stream of research has dealt with consumers' drivers for participating in viral marketing campaigns. Product involvement, self-enhancement, satisfaction as well as

customer commitment have repeatedly been identified as important motivators for consumers to engage in referrals (Hennig-Thurau et al. 2004). Albeit it should go without saying that consumers' perceptions of information value would influence the likelihood of them making a referral to their peers, only recently has this relationship been substantiated empirically (Pihlström and Brush 2008). It has also been demonstrated that peoples' concerns about how their actions will affect their image in the eyes of others influence their referral decision (Zhang et al. 2014). Cheema and Kaikati (2010) demonstrated that consumers' need for uniqueness, which is the desire to perceive oneself as unique but at the same time accepted as an individual member of society, has a negative influence on consumers' willingness to make referrals. Lastly, Hennig-Thurau et al. (2004) assert that social benefits are an important motivator for consumers to participate in viral marketing, which is in line with the findings of others (e.g., Berger 2013; Nahapiet and Ghoshal 1998) who claim that social capital – referred to as the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit (Nahapiet and Ghoshal 1998) – may very well be the most important reason why consumers engage in referrals. The rationale is that information, a crucial form of social capital, is the key through which people gain access to others' resources (Coleman 1988). Hence, social capital exists and governs relations among people, making the maintenance and creation of it critical to anyone's personal and professional advancement (Coleman 1988).

Despite these extensive and valuable contributions to literature, it is surprising to find that only little attention has been paid towards classical promotional tactics – i.e., tactics that have traditionally been applied in offline promotional campaigns – which may successfully affect consumer participation in viral marketing campaigns, even though previous research has pointed out that a more comprehensive understanding of the mechanisms driving referral behavior in online campaigns may simply be obtained by examining traditional promotional tactics from the offline world (Berger 2013). We therefore intend to address this research gap by examining the effects of scarcity and personalization on consumer referral behavior in a real world field study. Our focus lies on these specific promotional cues as prior research has demonstrated their link to factors which are important drivers of consumer referral engagement, namely product or information value and the need to reciprocate.

3.2.2 Scarcity in Promotional Campaigns

According to economic market theory, scarcity describes a state where ceteris paribus, the demand for an object exceeds its supply (Kemp and Bolle 1999). Research has demonstrated

that restrictions on an object's availability can have a positive effect on product preference, desirability, valuation and hence consumer decision-making (Amaldoss and Jain 2005; Inman et al. 1997; Van Herpen et al. 2009).

Practitioners claim that scarcity helps to create a “hype” and are increasingly turning towards it when implementing their promotional campaigns. Take for example the success story of Mailbox, the company that managed to accumulate over one million signups for its service within only six weeks, prior to even having released its product. Mailbox simply launched a landing page with a pre-signup option that emphasized how many other users were in line in front of the current visitor on the waiting list and therefore created a feeling of scarcity among potential customers (Techcrunch 2013). Even well established firms with access to large resources have turned to scarcity tactics. For example, the online retailer Amazon only offered its new kindle tablet in a limited edition before actually making it available to the wider public (Say 2013; Sharma 2013). In the context of online commerce, it has become very common to implement scarcity tactics by simply displaying promotional claims along the lines of e.g. “only 3 left in stock” (Amazon.com) or also “only 4 deals left” (Groupon.com).

Research suggests that scarcity evokes a state of physical agitation in which our sole focus becomes to fulfill the need in which we feel our freedom to be threatened (Brehm and Brehm 1981; Cialdini 1993a). However, literature on scarcity has diverged into two distinct streams which advocate peculiar differences in the causal effects of scarcity on consumers based on the origin of diminished availability: On the one hand, supply-based scarcity due to deliberate or accidental shortages in supply and on the other hand, demand-based scarcity due to excess social demand.

Supply-based scarcity is suggested to have a positive effect on product value and therefore consumer purchasing behavior (Inman et al. 1997; Lynn 1989; Zellinger et al. 1975). More specifically, supply-based scarcity affects perceived exclusiveness, which helps consumers fulfill their need for uniqueness (Van Herpen et al. 2009). According to uniqueness theory, consumers have the need to achieve moderate dissimilarity from others and one way of doing this is through self-identifying personal possessions, which means owning things that less people hold and hence are more exclusive, like e.g. the previously mentioned example of Amazon's kindle limited edition (Amaldoss and Jain 2005; Fromkin 1970; Hornsey and Jetten 2004; Snyder 1992).

On the other hand, demand-based scarcity arises primarily due to high amounts of prior purchases rather than deliberate supply limitations as in the case of supply-based scarcity (Van Herpen et al. 2009). It can positively influence consumer purchasing behavior and serves as a social validation mechanism that leads consumers to make inferences about social appropriateness, good quality and high product value (Bearden and Rose 1990; Kardes et al. 2004; Worchel et al. 1975). In the case of demand based scarcity, consumers do not aim at fulfilling their need for uniqueness through obtaining exclusive possessions that help them differentiate themselves from others as in supply- based scarcity. Rather, as bandwagon theory suggests, consumers strive to possess a good because people follow each other's behavior since they believe that others' choices reveal superior opportunities which they do not want to miss out on. Furthermore, excess demand serves as social validation which leads consumers to make inferences about social appropriateness as well as good quality and high product value (Van Herpen et al. 2009). Van Herpen et al. (2009) explain that consumers do not necessarily have to observe the behavior of others for these effects to unfold, seeing the outcome of their actions is sufficient (e.g. empty shelves). The previously exemplified story of Mailbox, where consumers know how many people signed up before them by seeing their position on the wait list, demonstrates just how effective demand-based scarcity can be in creating a “hype”.

Overall, previous research on scarcity has mainly focused on outcomes related to consumer purchase behavior in traditional offline settings (e.g., Inman et al. 1997; Suri et al. 2007). Solely from the work of Cheema and Kaikati (2010), who analyzed the influence of consumers' need for uniqueness on word of mouth engagement, one can infer that supply-based scarcity inhibits participation in electronic word of mouth. However, there is still little knowledge about how demand-based scarcity used within online viral marketing campaigns may affect consumer referral behavior.

3.2.3 Personalization in Promotional Campaigns

Personalization can be defined as the “[...] *adaptation of the marketing mix to an individual customer based upon the marketer's information about the customer*” (Montgomery and Smith 2009 p. 131). Specifically, in the context of the web, it relates to the “*company driven individualization of customer web experience*” (Allen et al. 1998 p. 32–33).

Personalization has existed long before the internet. Early discussions revolved mainly around segmentation and targeting (Petrison et al. 1993) and the first practical examples related to simply addressing people by name in mailings and surveys (Cox III et al. 1974). However, the

Internet has helped advance personalization in that it has made it easier than ever to tailor communication and offerings to consumers (Thorbjørnsen et al. 2002). Hence, the scope of application has grown from personalized greetings in communicating with consumers to, for example, tailored recommendations and offers in e-commerce and electronic news (Arora et al. 2008). Furthermore, it has become very common for firms of all sizes to tap into personalized communication in their promotional campaigns. Forkly for example built landing pages and provided interested consumers with personalized links and campaigns which could be shared with their friends and followers after registering for the service. As soon as three of his/her friends registered, the consumer would get early access to the service (Ries 2011; Smashmagazine 2011). Other campaigns draw on personal information which consumers provide in subsequent interactions to improve customer satisfaction by building a more personal interaction, for example, by addressing them by name (e.g., EyeEm).

Research on personalization has predominantly focused on three particular aspects. The first aspect is implementation methodologies that deal with how information is learnt about consumers (i.e., active or passive information collection) and may then be used to tailor communications and offerings (e.g., Dahan and Hauser 2002; Mobasher et al. 2000; Montgomery and Srinivasan 2002; Rossi et al. 1996). The second aspect of research relates to personalization's value to consumers and companies, such as higher customer satisfaction as well as increased profits (Arora et al. 2008; Miceli et al. 2007; Vesanen 2007). Lastly, more recent research has dealt with the boundary conditions of personalization, suggesting that the benefits of personalization need to exceed its costs to achieve a positive outcome for the consumer and the firm. More specifically, this means that the value generated for consumers (e.g., higher satisfaction) must be greater than the perceived costs related to the intrusion of their privacy (Ansari and Mela 2003; Montgomery and Smith 2009; Simonson 2005; White et al. 2008).

From a relationship marketing (RM) perspective, the practice of personalization helps interlink customers and marketers and build relationships (Imhoff et al. 2001; Simonson 2005; Vesanen and Raulas 2006). Therefore, personalization can be viewed as a RM investment. Literature has demonstrated that such RM investments influence consumer behavior and may result in superior seller performance (Moorman et al. 1992; Morgan and Hunt 1994; Sirdeshmukh et al. 2002). Although traditionally trust and commitment are claimed to mediate the effect of such RM investments on seller performance, more recent findings by Palmatier et al. (2009), while controlling for these two factors, show that in fact consumer

gratitude is a more significant mediator. The suggestion is that RM investments cultivate consumer feelings of gratitude, which in turn lead to gratitude-based reciprocal behaviors that result in an achievement of outcomes desired by the firm (Palmatier et al. 2009). Gratitude is a short-term state (Ben-Ze'ev 2001) and it is reciprocity's emotional core (Emmons and McCullough 2004). It arises when people feel themselves to be recipients of an "intentionally rendered benefit" (Emmons and McCullough 2004 p. 9) and leads to a psychological pressure to return the favor. This behavior is distinct from responses resulting from normative pressure (i.e., the norm of reciprocity), which is based on the notion that you have to help someone if they have helped you (Perugini et al. 2003). Instead, reciprocal behaviors in the case of RM investments are the response to an individual's emotions and feelings of gratitude (Palmatier et al. 2009).

Despite the considerable amount of research on personalization and its ubiquity within marketing communication in different forms, be it via personalized greetings or recommendations, to our surprise we still know little about its influence on consumer referrals of online promotion campaigns.

3.3 Research Model and Hypothesis Development

We derived our research model by adopting the word of mouth framework introduced by De Matos and Rossi (2008), which consists of the three sequential stages Manipulations → Antecedents → wom-activity. In line with this overarching framework, and as depicted in Figure 4, our research model sheds light on (1) the (main and direct) effects of scarcity and personalization on consumer referral propensity (H1/H3), (2) the role of offer value and consumer gratitude in mediating the preceding effects (H2/H4), and (3) the joint effects of scarcity and personalization on consumer's referral propensity (H5).

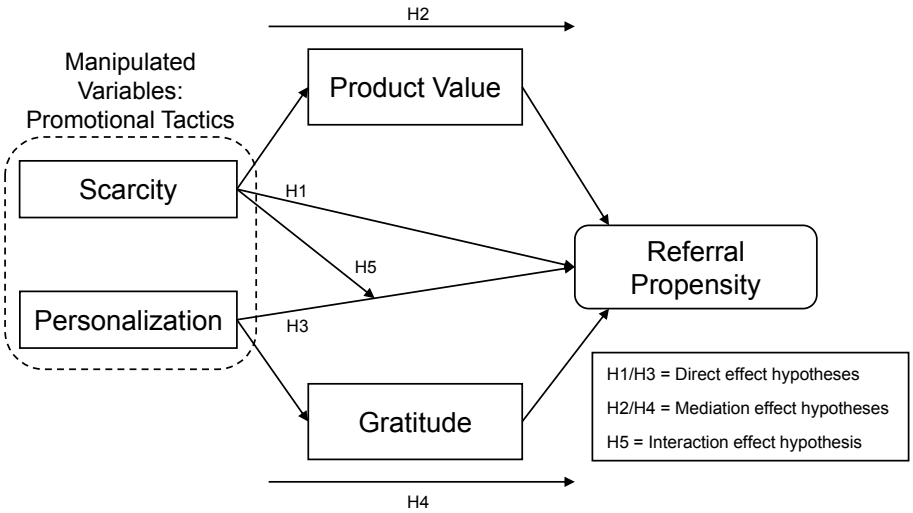


Figure 4. Research Framework

3.3.1 The Effect of Demand-based Scarcity on Consumer Referral Behavior

Literature suggests that scarcity triggers an automated thought-process which limits our ability to think clearly (Cialdini 1993a) and ultimately leads to higher product valuations due to the fact that people generally value things that are harder to attain more (Inman et al. 1997; Van Herpen et al. 2009; Worchel et al. 1975). It evokes a state of physical agitation in which our sole focus becomes to fulfill the need in which we feel our freedom to be threatened (Brehm and Brehm 1981). Although the emphasis in extant literature has been on reactions to reinstating this freedom in the context of purchasing behavior, we argue that under conditions of high scarcity, consumer referrals are an equally legitimate reaction.

Prior research has found that people (senders) share information with their peers (recipients) for social capital (Berger 2013; Coleman 1988; Nahapiet and Ghoshal 1998). Hence, it is likely that people who strive to build social capital by sharing information with their peers may be influenced in their referral decision by the perceived value of the information at hand. Thus, we argue that making an offer in a promotional campaign more scarce is likely to evoke a thought-process which can lead to higher valuations (Van Herpen et al. 2009; Worchel et al. 1975) of the offer and therefore also of the value of the information being shared. This in turn will increase the likelihood of a referral, as freedom is threatened in the sense of foregoing the possibility of sharing valuable information and therefore reaching the goal of building social capital. Our suggestions are in consonance with previous research that has revealed a positive relationship between perceived information value and consumer referral behavior (De Matos and Rossi 2008; Pihlström and Brush 2008). Based on this logic, one would infer that the

higher a sender's expectations of building social capital are the scarcer the offer of the promotional campaign being shared is, because the recipients from the sender's social network will recognize a relatively larger investment on his/her behalf when the message being shared is scarcer and therefore perceived to be more valuable (Coleman 1988).

It is important to note that consumers will have secured the offer for themselves before sharing it (e.g., like in the case of Mailbox by securing a position in the wait list), which is the way such campaigns are normally designed in practice. Thus, they need not worry about losing out on their own consumption opportunity. Capitalizing on this information advantage to build social capital therefore becomes a logical and important motive.

In sum, we expect that senders value the information they are sharing with their peers as higher when the offer in a promotional campaign is relatively scarcer due to social demand. At the same time, the very nature of the offer being so limited is likely to impose direct pressure on them to share the offer, as the information might become obsolete as time passes. Conversely, promotional campaigns with low scarcity due to social demand will appear less valuable because senders will not feel the pain of losing opportunities to build social capital within their network to the same extent. Hence, we expect that

H1. Consumers will be more likely to make the decision to refer a promotional campaign with high compared to low demand- based scarcity.

H2. Consumers' perceptions of offer value will mediate the effect of demand-based scarcity on their referral propensity.

3.3.2 The Effect of Personalization on Consumer Referral Behavior

Personalization on the web can lead to increased purchase intentions or other goals desired by the marketer (Ansari and Mela 2003; Arora et al. 2008; Miceli et al. 2007). A key precondition is that consumers perceive foregone privacy and utility derived from personalization to be well balanced and therefore not too intrusive (Montgomery and Smith 2009; Simonson 2005; White et al. 2008). We argue that receiving personalized messages from a company (e.g., a special offer for a new product, service or feature) on the one hand and giving up some personal information on the other hand strike such an optimal balance when consumers have either already shown interest by pre-registering for a company's service or when they have previously interacted with the same company in the context of other services and thus a relationship exists between the consumer and the marketer (e.g.,

consumers that have been using Amazon for ordering books and videos for years and now receive an offer regarding a new service, for example, video screening).

In these cases, privacy concerns oftentimes take a back seat and the benefits of personalized messages come to the fore. Addressing consumers by name then helps cultivate perceptions of them being the intentional recipient of “benevolence”, an essential precondition for gratitude to arise (McAdams and Bauer 2004). Therefore, we argue, consistent with previous empirical findings (Palmatier et al. 2009), that when a relationship between the marketer and the consumer pre-exists, personalization by name will arouse feelings of gratefulness because consumers will recognize a relationship investment by the marketer. These feelings in turn will increase consumers' need to engage in positive, gratitude-based behaviors and therefore result in a higher likelihood of compliance with subsequent requests made by the marketer (Goei and Boster 2005; McCullough et al. 2001).

In our research context, the effectuated gratitude will lead to a greater likelihood of complying with referral requests. In this situation, consumers' focus lies on the marketer (i.e., the firm providing the promotional offer) rather than the receivers of the referral. Tying into the results of several prior offline studies, Joinson and Reips (2007) for example showed a significant positive effect of addressing recipients by name on response rates in web based surveys.

It is most certainly a valid counter argument to suggest that consumers would be hesitant to share a promotional campaign with their peers if they need to worry about losing out on the opportunity themselves. However, as suggested earlier, in the context of such promotional offers, consumers normally have secured the offer for themselves prior to making the decision of referring it to their peers. Similarly, we believe that personalizing a promotional campaign through addressing the consumer by name will have no attenuating effect on consumers' perceptions of the offer's relevance to their peers. First, to the knowledge of the consumer, the shared offer which their peers receive will be without the personalized greeting. Second, as previously suggested, the consumer's primary focus lies on reciprocity based on gratitude towards the firm and not on the referral recipients. Hence, there is no reason why consumers should judge the relevance of the offer to their peers with more or other scrutiny compared to when personalization cues are absent.

In sum, we thus suggest that personalized campaigns are likely to lead to higher referral likelihood due to consumers' need to engage in gratitude-based reciprocal behaviors. Specifically, we expect that gratitude vis-à-vis the marketer will mediate the relationship

between personalized messages in promotional campaigns and consumer referral propensity. On the contrary, we would expect comparatively lower referral likelihood when promotional campaigns are not personalized. Accordingly, we hypothesize that

H3. Consumers will be more likely to refer a personalized than a not personalized promotional campaign.

H4. Consumers' gratitude vis-à-vis the marketer will mediate the effect of personalization on consumer referral propensity.

3.4 Empirical Study

3.4.1 Experimental Design and Procedures

We cooperated with the online media company *ecomedia*[2]. from Germany to conduct a randomized field experiment. Its true identity cannot be revealed due to confidentiality agreements. *ecomedia* is a mid-sized media holding operating more than 15 different e-commerce platforms. We agreed to conduct our study based a new online service named StyleCrowd, which gives individual style recommendations based on body characteristics, including the option to directly shop these recommendations at significant discounts. StyleCrowd at the time was in its pre-launch phase and heavily drew on viral marketing campaigns to collect consumer feedback and gain market traction.

We employed a 3 (scarcity: none vs. low vs. high) × 2 (personalization: presence vs. absence) between-subjects, full-factorial design. All three treatments of scarcity were combined with personalized and non-personalized cues on the main campaign landing page, resulting in a total of six experimental conditions (see Figure 5 and Figure 6 for two examples). The landing page promoted the new online service with a special offer, which allowed participants to secure early access and substantial discounts on the platform as well as premium membership for free. Aside from details about the offer, the main campaign landing page contained a video that explained the business idea, a proceed button, as well as a promotional statement (our manipulation) which altered in terms of scarcity (no, low, high) and personalization (personalized, not personalized) levels.

Consistent with the sampling and procedures in previous randomized field experiments (e.g., Burtch et al. (2015); Tucker (2014)), *ecomedia* sent email invitations to existing customers asking them to participate in the current study. Those who opted to participate could click a

[2] *ecomedia* is a pseudonym

web link in the email to start the process. Subjects were randomly streamed to different cells of our experimental design. Since the names and e-mail addresses of *ecomedia's* customers were accessible, they could be used for manipulating the personalization cues.[3]

The experiment proceeded in three major steps. First, before being forwarded to the main campaign landing page and being randomly assigned to one of the six experimental conditions, participants received the instruction to explore the promotional campaign of a new online service called StyleCrowd and to give feedback. After checking out the campaign website, all participants were asked to press a "Proceed" button (see Figure 5 and Figure 6). Second, after tapping the proceed button, participants were forwarded to a webpage and prompted to refer the offer to their friends via a share button that, when triggered, gave them the opportunity to log into their Facebook network or enter e-mail addresses of friends. Opting into this option thus resulted in a direct distribution of StyleCrowd's promotional campaign to their peers. This brief referral process ended with routing participants to a web page with the post-experimental questionnaire. Participants could also opt out via a non-share button[4] and were then directly forwarded to the site with the post-experimental questionnaire. In the last step, a post-experimental questionnaire asked participants to respond to questions measuring offer value, gratitude, control variables, manipulation checks, and several other variables (see Manipulations and Measured Variables). On the last page of the survey, subjects were debriefed and thanked for their participation.

[3] With our non-/personalization treatments, we thus study situations in which online consumers are prepared to be addressed by name such that privacy concerns can be expected to be low

[4] We equalized the presentation format of the share and non-share buttons, thus controlling for design and saliency effects

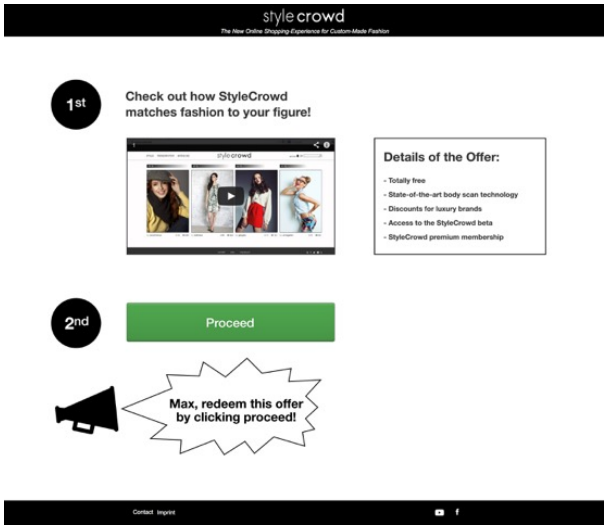


Figure 5. Main Campaign Landing Page (No scarcity, personalized condition)

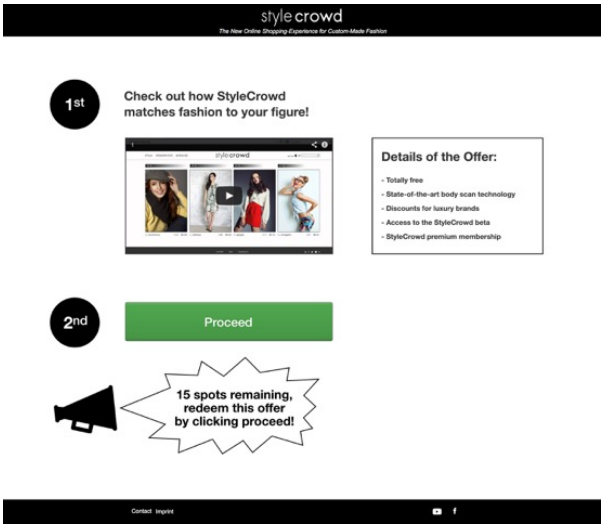


Figure 6. Main Campaign Landing Page (High scarcity, non-personalized condition)

3.4.2 Manipulations and Measured Variables

We followed Diab et al. (2008) and Barone and Roy (2010) to devise our manipulation of scarcity. Scarcity was manipulated by displaying the remaining availability of spots for the offer in a speech bubble (see Figure 5 and Figure 6) and specifying that it is to be redeemed on a first- come-first-serve basis. Our manipulation of personalization was based upon Porter and Whitcomb (2003) salutation manipulations, distinguishing between promotional claims that include (exclude) participants' first name. For a complete overview of all conditions and the embodiments of our manipulations, please view Figure 7.

Personalized	Scarcity: No	Scarcity: Low	Scarcity: High
No	redeem this offer by clicking proceed!	**100 spots** remaining, redeem this offer by clicking proceed!	**15 spots** remaining, redeem this offer by clicking proceed!
Yes	**Max**, redeem this offer by clicking proceed!	**Max**, **100 spots** remaining, redeem this offer by clicking proceed!	**Max**, **15 spots** remaining, redeem this offer by clicking proceed!

Figure 7. Experimental Conditions (Max as Placeholder Name)

To develop the stimuli for our studies, we conducted a pre-test in which 30 participants (56% females, M_{age} = 24.6) ranked the scarcity and personalization levels of our treatments. The manipulation check of scarcity showed that participants ranked the high scarcity condition as

significantly scarcer than the low scarcity ($F(1, 29) = 7.05$, $p < .001$) as well as the control condition ($F(1, 29) = 19.80$, $p < .001$). Furthermore, we measured consumers' perceptions of demand/ popularity as well as exclusiveness to ensure that our scarcity manipulations were perceived to be based on excess demand rather than supply limitations. Hence, we obtained popularity perceptions by adapting three items from Van Herpen et al. (2009) and exclusiveness perceptions by adapting three items from Franke and Schreier (2008). The observations revealed that consumers truly perceived the offer in the high scarcity condition to be more in demand (more popular) than that in the low ($F(1,29) = 4.989$, $p < .05$) as well as no scarcity condition ($F(1,29) = 20.044$, $p < .001$). Participants' assessment of the offers' exclusiveness also did not significantly differ between the high and low ($F(1,29) = 1.94$, $p > .1$) as well as the high and no scarcity conditions ($F(1,29) = 2.932$, $p > .1$). Lastly, participants ranked the personalized condition compared to the control condition as more personalized ($F(1, 29) = 11.62$, $p < .001$).

Our dependent variable (i.e., propensity to refer), in line with Stein and Ramaseshan (2014), was measured as a binary variable (referred vs. not referred) based on actual referral behavior during the field experiment. In consonance with Moe and Fader (2004), who measured purchase propensity in the context of website visits, we describe referral propensity as the probability of making a referral by defining a point estimator based on:

$$P\ (referral\ in\ Group\ Z) = \frac{\sum_{k=1}^{n} x_k}{n}$$

where Z refers to one of the six subgroups or conditions (e.g. no Personalization & Low Scarcity), n denotes the total amount of participants in the respective subgroup and x_k is a dichotomous variable which equals 1 when a participant made a referral and 0 if not.

Via clickstream data, we collected the number of clicks on the share/non-share buttons in the different experimental conditions. The mediators offer value and gratitude (vis-à-vis the marketer) were measured by adapting items from Suri and Monroe (2003) as well as Palmatier et al. (2009) respectively. In addition, the following control variables which have been identified as the most salient referral motives in extant literature were selected largely based on theoretical considerations: information privacy concern, product (i.e., fashion) involvement, market mavenism, need for uniqueness, perceived information relevance to others and image-impairment concerns. A 7-point Likert scale was adopted for all measures with anchors ranging from strongly disagree (1) to strongly agree (7). Information on all constructs and items can be found in Table 5 of the Appendix.

Confirmatory factor analysis results showed that all scales exhibited satisfactory levels of convergent validity. Moreover, discriminant validity requirements were met (Fornell and Larcker 1981), as each scale's average variance extracted (Awad and Krishnan 2006) exceeded multiple squared correlations. Since all latent variables displayed adequate internal consistency, they were averaged to form composite scores for subsequent statistical analyses. The construct correlation matrix is depicted in Table 6 of the Appendix.

As manipulation checks, besides rating perceived scarcity (i.e., "The offer advertised in the promotional campaign is scarce"), perceived popularity/ exclusiveness and personalization ("I felt personally addressed by the promotional campaign") on a 7-point Likert scale, participants were asked two closed questions in the post-experimental questionnaire: (1) Have you been addressed by name on the main campaign landing page? [Yes or No], and (2) How many free spots were indicated to be remaining when you viewed the campaign landing page? [Unlimited, 100, or 15 spots].

3.4.3 Sample Description, Control and Manipulation Checks

From the five hundred customers that *ecomedia* had invited to the study, 131 answered the invitation e-mail (response rate: 26.2%). Twelve participants (9.2%) were removed from the sample for the following reasons: Five subjects failed to complete the questionnaire and seven failed our attention filter/ self-report measure (Meade and Craig 2012). Hence, we used a sample of 119 subjects in the following analysis. Table 3 summarizes the descriptive statistics.

	Mean	StD	Min	Max
Demographics				
Gender (Females)	58.80%	49.42%		
Age	31.83	8.8	20	69
Internet Usage in years	7.9	3.6	5	18
Weekly Internet Time	19.68	21.16	2	50
Controls and Mediators				
Fashion Involvement	4.53	1.2	2	7
Privacy Concerns	2.34	0.82	1	7
Market Mavenism	3.42	1.59	1	7
Need for Uniqueness	3.59	1.64	1	7
Information Relevance Others	4.83	0.93	2	7
Image Impairment Concern	3.3	1.35	1	5.33
Offer Value	4.76	1.10	1	7
Gratitude	4.68	0.83	2	7
Dependent Variable				
Referral %	15.97%	36.78%		

Notes: means and standard deviations, N = 119

Table 3. Descriptive Statistics

Non-response bias was assessed by verifying that early and late respondents were not significantly different (Armstrong and Overton 1977). t-Tests on socio-demographics between the early (first 50) and late (last 50) respondents showed no significant differences ($p > 0.05$) indicating that non-response bias was unlikely to have affected the results.

To confirm the random assignment of subjects to the different experimental conditions, we performed several one-way ANOVAs. These analyses did not reveal any statistically significant differences in age ($F = 0.566$, $p > 0.05$), gender ($F = 0.724$, $p > 0.05$), weekly internet time ($F = 0.713$, $p > 0.05$), privacy concerns ($F = 0.916$, $p > 0.05$), product involvement ($F = 1.193$, $p > 0.05$), market mavenism ($F = 0.835$, $p > 0.05$), need for uniqueness ($F = 1.175$, $p > 0.05$), information relevance to others ($F = 0.497$, $p > 0.05$) or image-impairment concerns ($F = 1.182$, $p > 0.05$) between all 6 experimental groups, therefore confirming that the random assignment of subjects to the conditions was successful. We additionally controlled whether participants who triggered the share button also actually referred the promotional campaigns to their friends. A clickstream analysis revealed that all participants that pressed the sharing button also either logged into their Facebook network (89.47%) or entered e-mail addresses of friends (10.53%). Given that we addressed participants with their first names in the personalization conditions, we also checked whether participants' privacy concerns were low and whether these potential concerns affected their

referral behavior. Participant's privacy concerns were quite low across all conditions (M = 2.34) and were not significantly associated with their referral behavior (r = − 0.106, $p > 0.05$), confirming that privacy concerns had no negative impact on referral behavior in our promotional context. Finally, given that the service appears to appeal systematically more to females than to males, we analyzed whether males and females significantly differed in their referral behavior, but did not find a significant difference ($p > 0.05$).

The manipulation checks confirmed that participants in the high scarcity conditions (M = 4.56; SD = 1.01) assessed the number of spots remaining as being more limited than in the low (M = 3.13; SD = 0.96) and no scarcity (M = 2.06; SD = 0.78) conditions ($F = 53.07$, $p < 0.001$). The low scarcity condition was also experienced as being more limited than the no scarcity condition (all planned contrasts between high, low and no scarcity conditions: $F < 1$). Our measures to assert that scarcity was perceived to be caused by excess demand instead of limited supply were also confirmed, demonstrating that participants in the high scarcity condition (M = 5.2; SD = 0.85) did perceive the offer to be significantly more popular than in the low (M = 4.31; SD = 0.93) as well as no scarcity condition (M = 3.04; SD = 1.05). The results also suggested a statistically insignificant difference ($p > .1$) in participants' perceptions of the offer's exclusiveness between the high (M = 3.87; SD = 0.86), low (M = 0.92; SD = 1.05) as well as no scarcity condition (M = 4.01; SD = 0.79). Furthermore, participants in the personalization conditions (M = 5.64; SD = 0.99) felt to be addressed more personally than those in the non-personalization conditions (M = 2.25; SD = 0.83). Finally, we found that all subjects exactly matched our treatments regarding the two closed manipulation check questions for the six different conditions, implying that the manipulations were successful.

3.5 Results

3.5.1 Main Effect Analysis for Scarcity and Personalization

To test H1 and H3, we conducted a three stage hierarchical logistic regression on the dependent variable referral propensity (see Table 4). We first entered all controls and mediators (model 1), then the main effects (model 2) and finally the interaction effect (model 3). All three models were statistically significant at $p < 0.001$. The increase in Nagelkerke's R^2 from model 1 to model 2 was statistically significant ($p < 0.01$), leading us to use model 2 to test our main effects hypotheses.

	Model 1		Model 2		Model 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	-11.691***	3.067	-11.527***	3.287	-13.598***	3.724
Manipulations						
Scarcity			1.904**	0.690	4.136***	1.261
Personalization			1.699*	0.796	4.538**	1.449
Scarcity × Personalization					-4.923**	1.695
Controls & Mediators						
Gender	-0.035	0.575	0.491	0.664	0.479	0.723
Age	0.017	0.024	-0.006	0.028	0.006	0.028
Fashion Involvement	0.040	0.201	0.071	0.222	-0.030	0.244
Privacy Concerns	-0.106	0.170	-0.132	0.193	-0.061	0.218
Market Mavenism	0.252	0.199	0.237	0.233	0.323	0.275
Need for Uniqueness	0.011	0.182	-0.051	0.199	-0.087	0.207
Offer Relevance Others	0.067	0.289	0.267	0.331	0.046	0.351
Image Impairment Con.	-0.362	0.351	-0.394	0.380	-0.632	0.450
Offer Value	1.436***	0.383	1.377**	0.403	1.773***	0.474
Gratitude	1.001***	0.286	0.634*	0.313	1.614	0.349
Log likelihood	90.888		79.757		68.992	
Nagelkerke's R^2	0.602		0.669		0.728	
Omnibus Model χ^2	69.861***		80.992***		91.757***	

Notes: * $p < .05$; ** $p < .01$; *** $p < .001$, $N = 119$

Table 4. Logistical Regression on Dichotomous Variable Consumer Referral Propensity

The results of the logistical regression revealed a significant main effect of scarcity (b = 1.904, Wald statistic (1) = 7.628, $p < 0.01$) and of personalization (b = 1.699, Wald statistic (1) = 4.56, $p < 0.05$). Hence, consistent with H1, participants primed with scarcity were more likely to make a referral than those in the no scarcity condition. Likewise, participants in the personalized condition were more likely to share the promotional offer than those in the control group, in support of H3. Taken together, these results show that priming recipients in a promotional campaign with scarcity significantly increases the probability of them referring the offer to their peers. In a similar vein, addressing participants by name increased the likelihood that consumers referred the promotional campaign.

We conducted post-hoc tests to shed further light into the differences among the high, low and no scarcity conditions. Overall, as depicted in Figure 8, our findings show that participants primed with high scarcity are significantly more likely to make a referral than those in the low scarcity (29.70% vs. 12.80%, t = 4.11, $p < 0.05$) or the no scarcity condition (29.70% vs. 7.00%, t = 5.67, $p < 0.01$). However, we found no evidence that participants in the low

scarcity condition were significantly more likely to share the promotional offer than those in the no scarcity condition (t = 1.48, p > 0.05). These results show that scarcity cues make a difference in consumer referral propensity only when scarcity is high but not when it is low, revealing a boundary condition to the main effect of scarcity. Before further analyzing the joint effect of the cues, we turn to our mediation effect hypotheses H2 and H4.

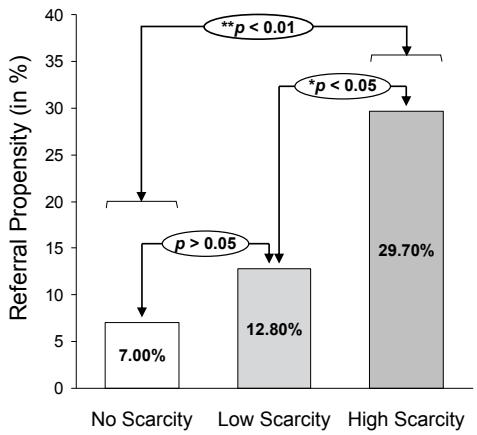


Figure 8. Effect of Scarcity on Referral Propensity

3.5.2 Mediation Analysis for Scarcity and Personalization

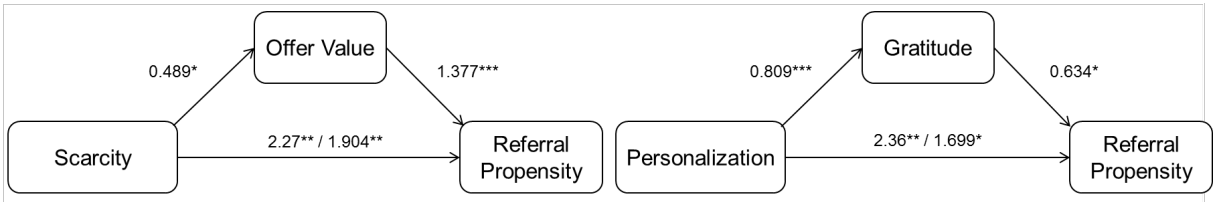
We hypothesized that scarcity's impact on participants' likelihood to engage in referrals would be driven by the sender's perceptions of offer value, while the mechanism underlying the effect of personalization on referral likelihood would be based on consumers' gratitude vis-à-vis the marketer. Thus, in a mediation model using bootstrapping with 10,000 samples and a 95% bias-corrected confidence interval, we tested the indirect effect of the promotional cues (i.e., scarcity and personalization) on referral propensity through offer value and gratitude. Two separate mediation analyses – one for each promotional cue – were performed, using the bootstrap mediation technique (PROCESS macro; Hayes (2013)).

First, to investigate the process driving the effect of scarcity on referral engagement, we entered offer value as potential mediator between scarcity and referral behavior. The indirect effect of scarcity on referral propensity through offer value was statistically significant (i.e., offer value significantly mediated the relationship: indirect effect = 0.674, standard error = 0.732, 95% bias-corrected confidence interval (CI) = [0.065, 1.624]), supporting H2. Furthermore, scarcity was positively associated with offer value (b = 0.489, p < 0.05), and higher offer value was associated with higher probability of making a referral (b = 1.377, p < 0.001; Figure 9), while scarcity's direct effect on referral propensity remained significant after offer value was entered into the model representing the case of a partial mediation (Hayes

2013).[5] These results thus showed that offer value significantly mediated the impact of scarcity on referral behavior, such that, as per our proposition, scarcity produced higher offer value, which in turn led to greater expectations of building social capital within one's social network, thus resulting in a higher likelihood of referring the online campaign.

Second, to examine the process underlying the effect of personalization on referral behavior, we entered consumer gratitude as potential mediator into a mediation model (Hayes 2013). The results showed that gratitude mediated the effect of personalization on referral propensity (indirect effect = 0.513, standard error = 0.729, 95% CI = [0.003, 1.543]), and that this effect was statistically significant as well. Personalization was positively associated with gratitude (b = 0.809, p < 0.001), and higher feelings of gratitude were associated with a higher likelihood of referral (b = 0.634, p < 0.05; Figure 9) while personalization's direct effect on referral behavior remained significant after gratitude was entered into the model indicating a partial mediation effect (Hayes 2013), in support of H4.[6]

In a supplementary analysis, we tested whether perceived offer value qualified as mediator for personalization and whether gratitude qualified as mediator for scarcity in the context of referral propensity. However, both indirect effects turned out to be insignificant (both p > 0.5).



Notes. Coefficients were computed based on mediation analysis using bootstrapping with 10,000 samples and a 95% bias-corrected confidence interval (Hayes 2013); all controls as well as manipulations were included in the analysis; the first coefficient on a given path represents the direct effect without the mediator in the model. The second coefficient represents the direct effect when the mediator is included in the model. *p<0.05, **p<0.01, ***p<0.001 one-tailed

Figure 9. Mediation Analysis

In sum, these results suggest that participants were more likely to make a referral of a personalized (vs. non-personalized) promotional campaign, because they had the urge to engage in gratitude-based reciprocity and therefore contributed back to the marketer by referring the promotional campaign.

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[5] In an ancillary analysis, we entered all controls simultaneously with offer value in a parallel multiple mediation, but no other indirect effect reached significance. These results cast doubt on alternative accounts

[6] We again also entered all controls simultaneously with gratitude in a parallel multiple mediation analysis, but no other indirect effect reached significance

3.5.3 Interaction Effect Analysis for Scarcity and Personalization

As indicated in model 3 of our logistic regression results (see Table 4), the main effects of scarcity and personalization on referral propensity were qualified by a significant two-way interaction ($b = -4.923$, Wald statistic (1) = 8.431, $p < 0.01$), suggesting that the effects of the promotional cues on referral behavior are contingent on the presence of each other. To further test H5, we conducted planned contrast comparisons to examine the conditional effects of personalization at different levels of scarcity (none, low, high). The results in Figure 10[7] highlight that participants primed with personalization are significantly more likely to refer the promotional offer than those in the no-personalization condition when scarcity is absent (18.75% vs. 0.00%, $F = 11.882$, $p < 0.01$). However, a significant difference in referral propensity between personalized and non-personalized campaigns did not emerge at low (22.07% vs. 16.67%, $F = 0.85$, $p > 0.25$) and, in particular, high (27.78% vs. 31.58%, $F = 0.122$, $p > 0.40$) levels of scarcity.

These results support H5 by showing that priming recipients in a promotional campaign with personalization does not significantly increase the likelihood of them referring the offer to their peers when high scarcity is present (in fact, the numbers suggest a slight decrease); it does however when scarcity is absent (see Figure 10). In other words, high scarcity resulted in a similar likelihood of referrals no matter whether the online campaign was personalized or not, whereas no scarcity led to greater referral engagement of personalized campaigns compared to non-personalized ones.

[7] The results for the low scarcity conditions were left out of Figure 10 for reasons of clarity

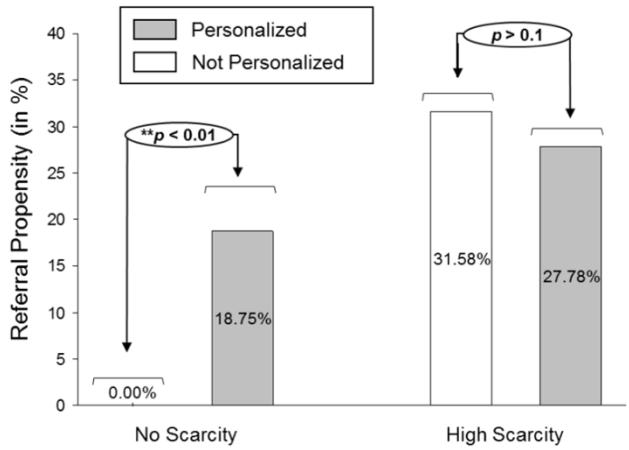

Figure 10. Interaction Between Personalization and Scarcity on Referral Propensity

3.6 Discussion

Viral marketing has become a key component of marketing strategy, not only due to its cost-effectiveness and broad reach, but also because consumers have come to perceive traditional online advertising as often irrelevant and therefore are increasingly turning towards alternative sources, most importantly word of mouth, to gather credible information about new products.

However, despite the substantial amount of research on consequences of viral marketing as well as factors that drive consumers' referral decisions, the role of classical promotional tactics in enhancing consumers' referral propensity has remained conspicuously absent from the literature. Therefore, this study aimed to shed light on the promotional tactics of scarcity and personalization, as prior research on these cues has demonstrated their influence on well-established drivers of consumer referrals.

Our findings support the premise that scarcity due to social demand has a positive causal effect on consumers' propensity to engage in referrals. Furthermore, we could specifically confirm that offer value acts as partial mediator for the effect of scarcity on consumer referral likelihood. Our underlying explanation is that consumers may believe to build more social capital with their peers while referring the offer, in particular because they perceive the value of the information they are sharing to be greater. At the same time, the fact that the offer is so limited also imposes direct pressure on them to share the offer as fast as possible, as the information at hand might become obsolete as time passes. As a boundary condition, we found that scarcity has to exceed an upper threshold value to be effective. While campaigns inducing low scarcity did not significantly differ in referral behavior compared to those with no scarcity at all, those with high scarcity had a strong effect indicating that scarcity is a

viable promotional tactic to increase referral propensity only after a tipping point has been reached.

We also found a positive and statistically significant effect of personalization on referral behavior which supported our premise that personalization of online campaigns can increase referral propensity, specifically in contexts of pre-existing relationships between consumers and the marketer. Consumer gratitude vis-à-vis the marketer thereby emerged as the key explanatory mechanism that underlies the impact of personalization on consumer referral behavior. Personalization is a relationship marketing investment which, when perceived as an intentionally rendered benefit towards the consumer, generates feelings of gratitude or gratefulness. These emotions in turn stimulate consumers' need to engage in gratitude-based behaviors leading to reciprocation by complying with requests made by the marketer (i.e., in our case referrals). Overall, our mediation results also suggest that scarcity's and personalization's effects were not due to privacy concerns, product involvement, market mavenism, need for uniqueness, offer relevance to others or image-impairment concerns, ruling out salient alternative accounts of referral engagement.

When considering the interaction between scarcity and personalization, we found that the positive effects of personalization on consumer referral propensity are overridden when scarcity cues are present. A plausible explanation for this crowding-out effect pattern is that scarcity does not only induce arousal and lead to a thought process which effectuates higher product valuations, but it also stimulates cognitive processing (i.e., assessing the offer's value) (Brannon and Brock 2001; Inman et al. 1997). Furthermore, the effectuated arousal results in a progressive decrease of the information used to perform the value assessment at the neglect of personalization cues which are less relevant in performing this task (Clee and Wicklund 1980; Ordonez and Benson 1997). Affective processing, which cultivates feelings of gratitude is consequently undermined, therefore wiping out the effects of personalization on consumer referral decisions.

Our study contributes to interactive marketing literature in expanding our understanding of the antecedents of ewom behavior in general and referral behavior in particular, as suggested by King et al. (2014). We shed light on mechanisms that may enhance referral propensity of first stage actors when seeding viral marketing campaigns, as more recent research insists that their critical role in the success of viral marketing campaigns has been overlooked by extant contributions (Pescher et al. 2014). We introduce previously underexplored catalysts of consumer referral behavior and provide a validated model to explain their interactions. The

results thereby illuminate the psychological processes underlying the promotional cues' effects, showing that these cues operate through different causal pathways to shape referral decisions. Our findings are in line with several previous studies which suggest that building social currency (Berger 2013; Hennig-Thurau et al. 2004; Nahapiet and Ghoshal 1998) as well as consumers' need to reciprocate in certain situations (Berger and Schwartz 2011; Cialdini 1993a; Sundaram et al. 1998) are key reasons for consumer referral engagement.

We also complement extant research on scarcity as a promotional tactic (Inman et al. 1997; Lynn 1989; Van Herpen et al. 2009; Worchel et al. 1975) by revealing its impact on consumer referral decisions and enhancing our understanding of the importance of the origin of scarcity, namely supply vs. demand based. Through providing insight into demand-based scarcity's positive effect on referral engagement, we extend the work of Cheema and Kaikati (2010), who suggest that supply-based scarcity decreases engagement in referrals due to consumers' urge to fulfill their need for uniqueness, and thus provide a more nuanced perspective on scarcity cues' influence on consumer referral behavior in promotional campaigns.

Lastly, we also bring more clarity to research on personalization through greetings which has hitherto shown mixed results. Our results demonstrate that personalized greetings can indeed have positive effects on consumers' referral propensity in contexts in which consumers can expect to be addressed by name (e.g., existing customers that receive information about a new product or service or consumers pre-registering for further information from a new venture) and thus when privacy concerns are less prevalent. This result is also in line with previous studies that found that personalized messages can have a positive impact on the marketer's desired actions (Heerwegh 2005; Joinson and Reips 2007). However, our work also reveals a novel boundary condition to personalization effects such that personalization cues (i.e., personalized greetings) are particularly effective when they operate independently from scarcity cues, yet are overridden when high scarcity is present.

While the preceding comments focus on theoretical contributions, our study's findings have also several practical implications. For firms seeking to increase referral likelihood of first stage actors when seeding their promotional campaigns, a precondition for word of mouth to unfold among subsequent actors, our findings imply that one needs to employ strong scarcity cues and that personalization can be neglected as long as high scarcity is a feasible option for implementation. In cases where high scarcity is not a viable option and there is a pre-existing relationship between the marketer and consumer (and potential privacy concerns are less prevalent), personalization should not be neglected but incorporated as facilitator of referrals

to increase the potential of subsequently going viral. Given these results, the business goals and products or services offered must be weighed and prioritized when deciding the types and combinations of promotional cues to be implemented in an online campaign. A freemium business model, for example, focusing on converting free users to paying premium customers might accentuate scarcity cues during promotional campaigns targeted at first stage actors to increase the urgency to act and therefore lay the basis for spreading the word around the campaign, while making do with little or no personalization. On the other hand, e-commerce driven business models that emphasize building long-term relationships with prospective customers might benefit from personalization cues in their campaigns at the neglect of scarcity which is often perceived as having a touch of puffery. In any case, recognizing this balancing act may help marketers make more informed trade-off decisions that best fit their own business model. Finally, marketers should extensively leverage peoples' need to build social currency in design decisions of their promotional campaigns to drive consumer referral likelihood and the awareness of their venture.

Despite the substantial theoretical and practical contributions, this study has some limitations which present avenues for further research. First, the nature of the service underlying the experiment naturally appealed more to females. Research on scarcity and personalization does not suggest the effectuated higher product valuations as well as feelings of gratitude to be a gender specific phenomenon, therefore leading us to expect similar effects in a context more pertinent to males. However, it has been put forward that females are generally more likely to disclose information than males (Dindia and Allen 1992), making it essential to test the validity of our findings in the context of more gender-neutral settings. Second, our study analyzed how scarcity and personalization affect referral propensity in the context of e-commerce with a special focus on fashion — a conspicuous and experience good. Future research should examine how these cues work in other business model contexts (e.g., freemium) and for different kinds of products (e.g., inconspicuous and search products). Third, our study focused on personalization settings in which consumers are prepared and can expect to be addressed by name in promotional campaigns and relationships between the marketer and consumer pre-exist. Future studies should however also investigate whether consumers are willing to share personalized campaigns to a similar extent when they don't know how the marketer collected personal information about them and there is no pre-existing relationship. Finally, the nature of the study only allowed for observing the effect of the promotional cues on referral decisions of first stage actors. Although, these referral decisions are a critical precondition to achieving virality, it is essential to understand how the

promotional tactics may affect second and later stage actors. The sheer fact that a person comes by a promotional offer through a referral may be interpreted as signal of higher social demand as proposed by Van Herpen et al. (2009) and therefore could be of material influence. According to Worchel et al. (1975), higher demand perceptions have a compounding effect on the positive relationship between scarcity and product valuation, leading us to expect an equally significant or greater influence of scarcity on the referral decision of later stage actors. Hence, future research needs to examine how scarcity effects referrals across different stages of dissemination.

We hope that our contribution helps advance our understanding of the antecedents of consumer referrals in the online context and fuels the respective stream of research on viral marketing among interactive marketing scholars, thus aiding marketers in devising effective online promotional campaigns which will trigger a viral loop around their offerings.

3.7 Appendix

Table 5. Measurement Scales

Construct	Item (all 7-Point Likert)
Perceived popularity Van Herpen et al. (2009) (α = 0.79, CR = 0.83, AVE = 0.74)	1. This offer is popular 2. I think that many people want to redeem this offer 3. This offer is redeemed well
Perceived exclusiveness Van Herpen et al. (2009) (α = 0.83, CR = 0.92, AVE = 0.74)	1. I perceive this offer as highly unique 2. This offer is one of a kind 3. This offer is really special
Perceived offer value Suri and Monroe (2003) (α = 0.83, CR = 0.84, AVE = 0.70)	1. I think that given this offer's attributes, it is a good value 2. At the advertised conditions, I feel that I am getting a good quality offer 3. If I redeemed this offer at the advertised conditions I feel I would be getting good value
Gratitude Palmatier et al. (2009) (α = 0.87, CR = 0.90, AVE = 0.81)	1. I feel grateful to *StyleCrowd* 2. I feel thankful to *StyleCrowd* 3. I feel appreciative to *StyleCrowd*
Information privacy concerns Sutanto et al. (2013) (α = 0.87, CR = 0.84, AVE = 0.79)	1. I am concerned with how information about me may be exploited by *StyleCrowd* 2. I am concerned that my privacy has been compromised by *StyleCrowd* 3. I am concerned that my personal information may be kept in a non-accurate manner by *StyleCrowd*
Product (Fashion) involvement Zaichkowsky (1985)	1. I am interested in reading articles about fashion and style
Market mavenism Feick Feick and Price (1987) (α = 0.85, CR = 0.88, AVE = 0.78)	1. I like introducing new brands and products to my friends 2. I like helping people by providing them with information about many kinds of products 3. My friends think of me as a good source of information when it comes to new products or sales
Need for uniqueness Tian et al. (2001) (α = 0.89, CR = 0.92, AVE = 0.81)	1. I collect unusual products as a way of telling people I'm different 2. When products or brands I like become extremely popular I lose interest in them 3. I have sometimes purchased unusual products or brands as a way to create a more distinctive personal image

Information relevance to others Hupfer and Detlor (2006)	1. I believe information about this offer could be relevant to my peers
Image-impairment concerns Zhang et al. (2014) (α = 0.81, CR = 0.85, AVE = 0.73)	1. I feel embarrassed for my buying mistakes 2. Consumers need to worry about how other people view them 3. Looking like a smart shopper is important for me
Perceived Scarcity	1. I think this promotional offer is scarce

Table 6. Construct Correlation Matrix

	1.	2.	3.	4.	5.	6.
1. Perceived offer value	1					
2. Gratitude	0.365*	1				
3. Information privacy concerns	-0.119	0.15	1			
4. Market mavenism	0.238**	0.225*	-0.236*	1		
5. Need for uniqueness	0.047	0.051	0.077	0.334*	1	
6. Image-impairment concerns	-0.021	0.081	0.148	-0.066	-0.088	1

Notes: * $p < .05$; ** $p < .01$, $N = 119$

4 How Scarcity and Social Proof Affect Online Referrals

Title

Designing Viral Promotional Campaigns: How Scarcity and Social Proof Affect Online Referrals

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Abstract

Online referrals have become an important mechanism in leveraging consumers' social networks to spread firms' promotional campaigns and thus attract new customers. However, despite a robust understanding of the benefits and drivers of consumer referrals, only minimal attention has been paid towards the potential of classical promotional tactics in influencing referral behavior. Therefore, this study examines scarcity and social proof, two promotional cues which are linked to extant referral literature and are of great practical relevance, in the context of a randomized online experiment with the German startup Blinkist. Our analysis reveals that scarcity cues affect consumers' referral propensity regardless of the presence of social proof cues, but that social proof cues amplify scarcity's effect on consumer referral propensity. We demonstrate that consumers' perceptions of offer value drive the impact of scarcity on referral likelihood and illuminate how social proof moderates this mediating effect.

Keywords

E-business, Electronic Word of Mouth, Consumer behavior, Online Promotional Campaigns, Scarcity, Social Proof, Perceived Offer Value

4.1 Introduction

Recently, as e-commerce penetrates people's everyday life, firms are increasingly relying on online referrals when generating awareness and acquiring new customers for their offerings. Against the backdrop that consumers are being deluged with traditional advertising, which is causing its effectiveness to fade (Porter and Golan 2006), interpersonal communication between consumers (i.e., referrals) has become a popular channel to spread marketing messages and attract potential customers (Todri and Adamopoulos 2014). The objective is to leverage consumer's social networks in order to promote and amplify the firms' marketing messages by encouraging users to pass along information to their peers (i.e. make referrals). Online referrals are peculiar in the broader context of electronic word of mouth (ewom), which also encompasses the articulation of opinions and reviews on online platforms like, for example, virtual online communities (Hennig-Thurau et al. 2004). Several studies have demonstrated that consumers' choices may be significantly influenced by each other and that word of mouth is perhaps the most important and credible source of information in consumer decision making (Brown and Reingen 1987; Chakravarty et al. 2010). The practice that focuses on generating campaign referrals not only through first stage (i.e. consumers that have received a message directly from the provider) but also second stage actors (i.e. consumers that have received a message from another consumer that has referred it to them) is also called viral marketing (Pescher et al. 2014). Firms that manage to design viral promotional campaigns benefit from cost efficiencies, broad reach and high credibility by capitalizing on the notion that consumers attribute higher credibility to information received from other consumers than from traditional advertising (Godes and Mayzlin 2004). Hence, it is not surprising that especially IT startups which usually neither possess significant brand equity nor drown in credibility rely on online referrals when spurring awareness around their offerings. Companies such as Groupon, Instagram, Spotify or also Pinterest, which has managed to grow its monthly unique visitors from 40,000 to 3.2 million users in only one year, are more recent examples that have managed to harness the power of online referrals to their advantage (Dörr et al. 2013; Techcrunch 2013).

Extant IS and marketing literature highlight the impact of ewom and viral marketing on firm level outcomes such as sales (e.g., Chen et al. 2004; Clemons et al. 2006; Gu et al. 2012; Trusov et al. 2009) as well as individual level outcomes related to consumer decision-making (e.g., Bickart and Schindler 2001; Chevalier and Mayzlin 2006a; Dierkes et al. 2011; Gauri et al. 2008). Furthermore, scholars have paid great attention towards the design of referral-incentive systems (Biyalogorsky et al. 2001; Ryu and Feick 2007; Shi et al. 2012), as well as

content characteristics (e.g., Berger and Milkman 2012; Berger and Iyengar 2012; Stephen and Berger 2009b) and motives that lead consumers to engage in referrals (e.g., Angelis et al. 2012; De Matos and Rossi 2008; Hennig-Thurau et al. 2004). However, hitherto minimal attention has been paid towards classical promotional tactics that may amplify consumer referrals, albeit they have proven effective in influencing consumer behavior in the offline world and have become common practice there. For example, to amplify consumers' purchase motivation, the online retailer Amazon created a sense of scarcity by only offering its new kindle tablet in a limited edition before actually making it available to the wider public (Sharma 2013). Despite the practical influence of such classical promotional cues and Berger (2013)'s suggestion that an enhanced understanding of communication mechanisms affecting extant referral drivers may simply be obtained by examining traditional promotional tactics from the offline world, little empirical work has followed up on the subject.

Our research intends to fill this gap by examining the effects of scarcity cues (i.e., the deliberate shortening of a good's availability and the communication thereof), which are often embedded in the websites of e-businesses as part of their promotional campaigns, on consumers' propensity to engage in referrals. Furthermore, we shed light on social proof cues (i.e., the deliberate communication of the popularity or high demand of a good) as moderator for this effect. We focus on scarcity, because research on this cues has demonstrated its influence on a factor which literature considers particularly critical to referral engagement, namely product or information value (Frenzen and Nakamoto 1993; Pihlström and Brush 2008; Sundaram et al. 1998). Social proof is examined as moderator because research has insinuated that perceptions of a good's popularity or prior demand have a significant influence on the scarcity-perceived product value relationship (Van Herpen et al. 2009; Worchel et al. 1975). From a practical perspective, both promotional tactics have become popular among well established firms like Amazon.com as well as nascent ventures such as Mailbox alike when generating awareness and attracting new potential customers and they are frequently deployed together (Nextshark 2013; Sharma 2013; Techcrunch 2012). Despite the broad use of such promotional tactics, however, it is surprising to find that practical recommendations on the effect of scarcity and social proof on referral behavior are still limited, leaving practitioners puzzled and without guidance. Taken together, the objective of this study is therefore to address these gaps guided by the following research questions:

(1) What impact do scarcity cues embedded in the promotional campaigns of e-businesses have on consumers' referral propensity?

(2) How do social proof cues affect the impact of scarcity cues on consumers' referral propensity?

This study contributes to IS and marketing literature on ewom in several important ways. First, we seek to shed light on the potential of promotional tactics in influencing consumer referral decisions and therefore expand our understanding of the antecedents of consumer referrals in online environments. More specifically, we analyze the effectiveness of scarcity cues embedded in the promotional campaigns of e-businesses in enhancing consumers' referral propensity. Our study takes place in the context of a randomized online experiment conducted with the company Blinkist, a German startup that is set to deliver summaries of nonfiction books' key insights in a made for mobile format to consumers in over 100 countries all over the world. We thus analyze consumers' actual referral behavior in a real world context, unlike many other studies which measure referral or sharing intent (e.g., Brown et al. 2005; Noone 2012), a more subjective construct. Second, we illuminate the causal mechanism behind scarcity's effects on consumer referral decisions and in doing so expand the investigation of psychological processes in the ewom literature. Finally, our study examines how social proof cues, which are popular and are often combined with scarcity in practice, affect the causal pathway through which scarcity operates when shaping consumer referral decision, thereby further explicating a moderator which is of profound practical as well as theoretical relevance.

This paper is organized as follows. In the next section, we review prior literature on viral marketing and online referrals. We then draw on scarcity literature to round up the theoretical foundation of our research model. The following section presents the hypotheses regarding the effect of scarcity cues on consumer referral decisions, including the mediating mechanism through perceived offer value, as well as the moderating effect of social proof. The subsequent section describes the research methodology used within our experimental study, followed by our data analysis and the results of hypothesis testing. Finally, we discuss our findings, implications and directions for further research. The last section concludes our paper.

4.2 Theoretical Background

4.2.1 Viral Marketing and Drivers of Consumer Referral Behavior

Viral marketing is the practice of deliberately exploiting consumers' social networks by encouraging them to make referrals to their peers (i.e., forward a provider's marketing messages) (Leskovec et al. 2007). In practice, companies are increasingly paying attention

towards the design of viral campaigns mainly for two reasons: cost effectiveness and broad reach. On the one hand, the rise of social networks through platforms such as Facebook, Twitter or LinkedIn, which have not only made it possible to share information with people outside one's direct network but have also simplified the process of resharing information down to a click, has contributed largely to the success of viral marketing in rapidly reaching a broad audience (Stein and Ramaseshan 2014). On the other hand, cost-effectiveness resulting from the fact that consumers are more likely to pay attention and are stronger influenced by each other than via traditional advertising has made viral marketing all the more attractive (Godes and Mayzlin 2004; Leskovec et al. 2007; Wagner et al. 2013; Wagner et al. 2014). Furthermore, companies drawing on viral marketing do not only benefit from higher credibility that consumers attribute to messages from their peers compared to direct messages from the provider, but it has also been demonstrated that customers who are acquired through referrals tend to be more loyal and therefore more profitable (Trusov et al. 2009).

An often cited success story of viral marketing is the online file hosting service Dropbox, which managed to implement an effective referral system that lead to a surge in its customer base from 100,000 to 4 million in only 15 months. Dropbox simply encouraged referrals by offering up additional storage for customers that successfully brought on friends (Veerasamy 2014). The emergence of social media has played an important role in making it easier and faster to implement campaigns that can go viral (Stein and Ramaseshan 2014). Companies like Facebook, Twitter or LinkedIn provide platforms that make it very simple to share information with people that reach way beyond one's immediate network. Against this backdrop, the popularity and practical relevance of viral marketing has grown exponentially among companies of all sizes. More recently, firms build minimal web-based landing pages around their promotional offerings and then spread links to these over social networks when implementing their viral marketing campaigns (Ries 2011; Say 2013). For example, by drawing on this method, the nascent venture Mailbox managed to accumulate over one million new signups over a period of six weeks without even having released its product (Techcrunch 2013).

Research has paid great attention towards the consequences of viral marketing on firm-level outcomes such as sales or revenue (e.g., Chen et al. 2004; Trusov et al. 2009). Similarly, it has been demonstrated on the individual level how consumers' decisions like for example usage continuance and loyalty (Dierkes et al. 2011; Gauri et al. 2008) or also purchase decisions (e.g., Bickart and Schindler 2001; Dellarocas 2003) may be positively influenced.

A comprehensive amount of research has also dealt with the drivers of consumer referral behavior on the individual level. Product involvement, self-enhancement, satisfaction as well as customer commitment have been repeatedly identified as important motivators for consumers to engage in referrals (Benlian 2015b; Bowman and Narayandas 2001; De Matos and Rossi 2008; Maxham III and Netemeyer 2002; Moldovan et al. 2011). Albeit it should go without saying that consumers' perceptions of information value would influence the likelihood of them making a referral to their peers, only recently has this relationship been empirically substantiated (Pihlström and Brush 2008). Other scholars have put forward that people are concerned whether their actions will impair or enhance their image in the eyes of others (Leary and Kowalski 1990) and that this will affect their referral decision (Zhang et al. 2014). Cheema and Kaikati (2010) demonstrated that consumers' need for uniqueness, which is the desire to perceive oneself as unique but at the same time accepted as individual member of society, has a negative influence on consumers' willingness to make referrals. Shi et al. (2012) suggest that successful referral incentive systems need to be designed with caution and take into account the dynamics of social norms that consumers may be in conflict with when making a referral, for example because the financial reward might not be evenly split between the sender and the receiver of the referral. Lastly, Hennig-Thurau et al. (2004) claim that social benefits are an important motivator for consumers to participate in viral marketing, which is in line with the findings of others (e.g., Berger 2013; Nahapiet and Ghoshal 1998) who suggest that social capital — referred to as "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (Nahapiet and Ghoshal 1998 p. 243) — may very well be the most important reason why consumers engage in referrals. The rationale underlying this notion is that information, a crucial form of social capital, is the key through which people gain access to others' resources (Coleman 1988; Tsai and Ghoshal 1998). Hence, social capital exists and governs relations among people, making the maintenance and creation of it critical to anyone's personal and professional advancement (Coleman 1988).

Despite these valuable contributions to literature, it is surprising to find that only little attention has been paid towards classical promotional tactics which may successfully enhance consumer referral propensity. Merely Berger (2013) acknowledges that an analysis of traditional promotional tactics from the offline world may reveal novel insights into further drivers of consumer referral behavior. However, to the best of our knowledge this call for research has remained largely unanswered hitherto. Furthermore, it is important to note that the context of e-business is very distinct and different from traditional offline business in

several aspects, indicating that it may be negligent to simply assume that findings regarding proven promotional tactics from the offline world are universally applicable and hence transferrable to the online context. Numerous studies have demonstrated that consumers' attitudes and behavior in online environments are very different from those in the offline world especially due to the absence of experiential information (Adomavicius et al. 2015; Degeratu et al. 2000; Kim and Krishnan 2015; Shankar et al. 2003). The absence of such information for example leads to greater restrictions in terms of consumers' abilities in assessing product availabilities in online shopping environments and thus, for better or for worse, effects purchase behavior (Jeong and Kwon 2012). Therefore, we intend to address this research gap by examining the effects of scarcity and a key moderator, namely social proof, specifically in the context of online promotional campaigns of e-businesses. These two tactics are not only of great practical relevance and are often deployed simultaneously but furthermore are also linked to well established drivers of referral literature.

4.2.2 Scarcity as Promotional Tactic

Scarcity describes a state where a shortage exists because the demand for an object exceeds its supply (Kemp and Bolle 1999). According to research, this unavailability may increase an object's desirability and its perceived value, hence significantly influencing consumers' decisions (Amaldoss and Jain 2005; Inman et al. 1997; Van Herpen et al. 2009).

In practice, it has become very popular for firms to incorporate scarcity in promotional campaigns when wanting to create a "hype" around their product. The nascent venture Mailbox for example simply launched a landing page with a pre-signup option that emphasized how many other users were in line in front of the current visitor on the waiting list and therefore created a feeling of scarcity among potential customers. This led to over one million signups for its service within only six weeks (Techcrunch 2013). However, also more established firms are increasingly turning to scarcity tactics, like the example of the online retailer Amazon that initially only offered its new kindle tablet as limited edition shows (Sharma 2013). Furthermore, it has become very common in e-commerce to implement scarcity tactics by simply displaying promotional claims like "only 3 left in stock" (Amazon.com) or also "only 4 deals left" (Groupon.com).

Research states that scarcity evokes a state of physical agitation in which our sole focus becomes to fulfill the need in which we feel our freedom to be threatened (Brehm and Brehm 1981; Cialdini 1993a). However, literature differentiates between two types of scarcity based on the cause of limited availability. On the one hand, supply-based scarcity, which originates

from deliberate supply limitations (i.e. limited production volumes) like in the case of the limited edition of the Amazon kindle (Verhallen and Robben 1994). This type of scarcity has been attributed positive effects on perceived product value as well as consumer purchasing behavior (Inman et al. 1997; Lynn 1989; Zellinger et al. 1975). According to uniqueness theory, the underlying rationale is that supply-based scarcity affects perceived exclusiveness, a construct that helps consumers fulfill their need to achieve moderate dissimilarity from others through self-identifying personal possessions (i.e., owning things that are more unique) (Fromkin 1970; Hornsey and Jetten 2004; Snyder 1992). Hence, the perceived value of a product decreases when more people own it because consumers are less successful in the pursuit of fulfilling their need for uniqueness (Amaldoss and Jain 2005).

On the other hand, demand-based scarcity arises primarily due to high amounts of prior purchases rather than deliberate supply limitations (Deval et al. 2013; Gierl and Huettl 2010). In this case, scarcity may also positively influence consumer purchasing behavior (Van Herpen et al. 2009; Worchel et al. 1975). However, instead of affecting perceived exclusiveness, demand-based scarcity serves as social validation mechanism and leads consumers to make inferences about social appropriateness, good quality and high product value (Bearden and Rose 1990; Kardes et al. 2004). A plausible explanation for this phenomenon is that people tend to follow each other's behavior because they believe that others' choices reveal superior products that they do not want to miss out on (Van Herpen et al. 2009). Van Herpen et al. (2009) for example, demonstrate in multiple experiments that it is sufficient for consumers to see the outcome of others' actions (i.e., reduced availability signals such as empty shelves) for higher product valuations to occur. They also provide evidence for the existence of the relative scarcity concept by demonstrating how consumers choose products which are clearly popular and at the same time less available at the point of purchase. Relative scarcity emphasizes the notion that the effect of scarcity on consumers' product value perceptions does not only depend on how much of an object is available but also how much of it exists at the time of purchase compared to the past (Gurr 1970; Worchel et al. 1975). Thus, consumers' beliefs of prior demand are an important moderator for the effect of demand-based scarcity on their product value perceptions.

In practice, e-commerce companies leverage the fact that people tend to follow each other's behavior (i.e., bandwagon effects) to influence consumers' decisions by implementing so-called implicit and explicit social proof cues that indicate product demand and popularity (Amblee and Bui 2011; Amblee and Bui 2012; Cialdini 1993a). Implicit social proof cues are

frequently implemented as banners and may highlight what prominent media the product has been featured in, such as in the case of the multibillion dollar online lodging service airbnb.com in its early days. This may lead to inferences about a larger audience that knows about a new good or offer and hence suggests greater popularity (Kissmetrics.com 2014). Explicit social proof cues on the other hand are frequently implemented as purchase counters like on groupon.com or also as waiting lists as in the case of Mailbox (Techcrunch 2011).

Despite the substantial contributions to literature on scarcity effects, the focus hitherto has almost exclusively been on consumer purchase behavior in traditional offline settings (e.g., Inman et al. 1997; Suri et al. 2007) and less on online referral behavior. One notable exception is Cheema and Kaikati (2010) who analyzed the influence of consumers' need for uniqueness on their willingness to engage in ewom, indicating that supply-based scarcity hampers participation in ewom as it is in conflict with consumers' pursuit for uniqueness. Nevertheless, there is still a research gap in how demand-based scarcity within online promotional campaigns of e-businesses affects consumer referral behavior. Furthermore, albeit social proof is an established promotional cue that has been examined extensively in the offline context (e.g., Cialdini 1993a; Simons 1976) and it has become ubiquitous in the context of e-commerce (Kissmetrics.com 2014), to the best of our knowledge, it has not been examined in conjunction with scarcity in online settings.

4.3 Research Model and Hypotheses Development

Our research model depicted in Figure 11 illuminates (1) the (main and direct) effect of scarcity on consumer referral propensity (H1), (2) the role of perceived offer value in mediating the effect (H2), and (3) social proof for moderating the preceding mediating effect (H3).

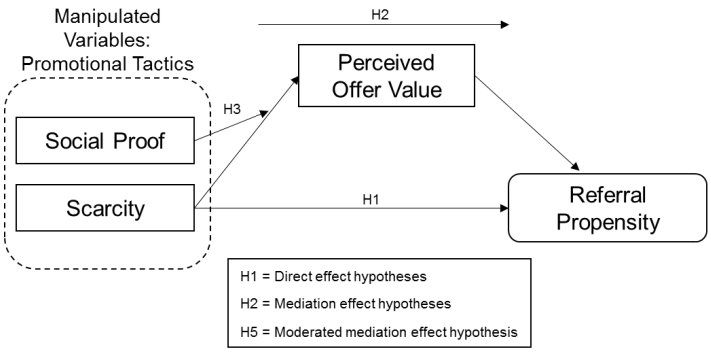


Figure 11. Research Framework

4.3.1 Demand-based Scarcity and Consumer Referral Behavior

Research has demonstrated how scarce products may lead to higher product valuations and hence positively affect consumer purchase behavior because people generally value things that are harder to attain more (Inman et al. 1997; Van Herpen et al. 2009; Worchel et al. 1975). Furthermore, it has been suggested that scarcity triggers an automated thought-process and that it induces a state of physical agitation in which our sole focus becomes to fulfill the need in which we feel our freedom to be threatened, for example by engaging in a purchase (Brehm and Brehm 1981; Cialdini 1993a). We propose that under certain circumstances in which opportunities for building social capital are threatened to be squandered, referrals are an equally legitimate reaction.

Consumers pass along information to their peers to build and maintain social capital because it is critical to their personal and professional advancement (Berger 2013; Coleman 1988; Koch 2015; Nahapiet and Ghoshal 1998). Thus, we argue that the referral decision of consumers who strive to build social capital should also be influenced by the value of the information they possess. Incorporating scarcity cues in a promotional campaign is likely to trigger a thought-process which leads consumers to higher valuations of the offer and hence the information at hand (Van Herpen et al. 2009; Worchel et al. 1975). This in turn will increase their referral propensity because they may feel their freedom to be threatened in the sense of forgoing the possibility of sharing valuable information and therefore pursuing their need to build social capital with their peers. These propositions are in line with the findings of Pihlström and Brush (2008) who found a positive relationship between perceived information value and consumer referral likelihood. In other words, we suggest that a sender's expectations of building social capital are greater when the offer of the promotional campaign being shared is scarcer, simply because the recipients of the referral will recognize a relatively larger investment on behalf of the sender when the message being shared is scarcer and hence perceived to be more valuable.

This argument does not hold true in the case of supply-based scarcity particularly as it would be highly questionable why a consumer would share a scarce offer instead of hoarding it for themselves. As literature claims, supply-based scarcity is focused on enhancing perceived exclusiveness to help consumers fulfill their need for uniqueness (Moldovan et al. 2011; Van Herpen et al. 2009). Sharing an offer in such situations would be counterproductive because, according to Amaldoss and Jain (2005), the more people own a good the less exclusive and

hence valuable it becomes. Therefore, the findings of Cheema and Kaikati (2010) regarding the referral inhibiting effects of consumers' need for uniqueness are no surprise.

However, demand-based scarcity is not focused on perceived exclusiveness or aiding consumers in fulfilling their need for uniqueness (Worchel et al. 1975). Consumers perceive goods that are scarce due to high demand as more valuable because they may make inferences about social appropriateness or superior product quality (Bearden and Rose 1990; Kardes et al. 2004). As bandwagon theory suggests, they may also simply feel the urge to do what others do and do not miss out on an opportunity (Van Herpen et al. 2009). It is not imperative that consumers directly view the actions of others for these effects to arise, viewing the outcomes or appropriate signals of prior demand (i.e., consumption), like for example empty shelves, is sufficient (Van Herpen et al. 2009). Furthermore, in practice consumers normally have secured an offer for themselves before referring it to theirs peers, like the example of Mailbox where one receives notice of one's own wait list position shows. We therefore relate to situations where consumers need not trade-off benefits and downsides of losing or maintaining their own consumption opportunity. Thus, it is a logical motive for consumers to build on such an information advantage to generate social capital.

Based on the preceding suggestions, we expect that consumers value information they refer to their peers more when the offer in a promotional campaign is comparably scarcer due to social demand. In particular, this is likely to be the case because consumers believe they are providing their peers access to a popular offer which they otherwise would not have had access to and hence would have missed out on. The fact that this offer is scarce further amplifies the value perceptions of the information being shared as it has been demonstrated that people generally tend to assess the value of an object to the extent of its unavailability. In addition, the demand-induced shortage of the offer also imposes a direct pressure on consumers to react by referring the information to their peers before it becomes obsolete. On the contrary, we expect that offers which are not scarce due to social demand do not stimulate the same behavioral responses, as the perceived losses associated with foregoing an opportunity to build social capital is relatively small. Hence, we expect that

H1. Consumers will be more likely to refer an online promotional campaign with compared to without demand-based scarcity.

H2. Consumers' perceptions of offer value will mediate the effect of demand-based scarcity on their referral propensity.

4.3.2 Social Proof as Moderator for the Mediation Effect of Perceived Offer Value

H1 and H2 propose that scarcity encourages consumer referrals due to the potential gains in social capital, which are higher when an offer is less accessible and hence more valuable. However, extant research posits that consumer's perceptions of prior demand are an important moderator for how strongly scarcity leads to more favorable valuations (Van Herpen et al. 2009). The suggestion is that when assessing the scarcity of an object it is not only important for consumers to know how much of it exists at the time they are to for example make a purchase decision. It is also critical for them to understand how much of the object exists at that point in time compared to the past to determine the extent of scarcity (Worchel et al. 1975). Hence, any cues which provide information on how strongly the availability has been reduced over time may influence consumers' perceptions of scarcity.

In the context of e-commerce, so-called social proof cues have been claimed as an effective cue in influencing consumers' perceptions of demand or popularity regarding a particular product or offer by communicating either explicit (e.g., purchase counters) or implicit (e.g., as seen in media banners) signals of prior consumption behavior (i.e., amount of people that have already purchased a particular product or redeemed a specific offer) (Amblee and Bui 2011; Amblee and Bui 2012; Veit et al. 2014). Implicit social proof cues have a distinct benefit over explicit ones in that they manipulate relative demand perceptions and thus may be effective from the very start without having to reach a certain threshold of prior purchases. The underlying rationale is that in the absence of social proof cues, but even in their presence, consumers' prior demand perceptions may vary greatly. Hence, implementing an explicit social proof cue like a counter indicating the number of previous buyers may have a positive effect on one consumer to whom that specific number seems high or sufficient but could also result in a negative effect with another to whom that particular number may seem low. Furthermore, even if firms were to manipulate this counter by setting it to a very high number they may be confronted with issues regarding the credibility of their claims. Thus, implicit social proof cues offer an effective and credible alternative as they allow to manipulate prior demand perceptions by signaling to the consumer that a potentially large audience has heard of this particular offering, hence leaving the definition of what is "large" to each person individually.

Thus, based on the notion that information on how availability has been reduced over time influences consumers' scarcity perceptions, we argue that when scarcity is combined with implicit social proof cues, which is often the case in practice (e.g., in promotional campaigns

of many e-businesses), its positive effect on the offer's perceived value is amplified. This is the case because consumers are likely to attribute great importance to signals that indicate the popularity of the offer and hence let them better understand how the availability of the offer has been reduced. More specifically, this additional information regarding the offers' popularity enables them to make inferences about what the offer's availability was in the past compared to now and aids them in reducing any decision uncertainties they may have (Gurr 1970; Worchel et al. 1975).

In sum, we thus suggest that campaigns including demand-based scarcity cues lead to higher referral likelihood when implicit social proof cues are present compared to when they are absent due to higher offer valuations. Therefore, we hypothesize that

H3. Social proof moderates the mediating effect of perceived offer value on the relation between scarcity and referral propensity, such that the mediated effect of scarcity on referral propensity through perceived offer value is amplified when social proof is present.

4.4 Research Methodology

4.4.1 Experimental Design and Treatments

We cooperated with a German startup named Blinkist to conduct a randomized online experiment. Blinkist is a globally operating popular online service that provides summaries of nonfiction books' key insights and delivers these via text or audio through its website as well as its iPhone and Android application. The venture has been featured by many famous media outlets such as Forbes, Techcrunch and others. The online experiment focused on testing different minimal landing pages regarding their referral effectiveness so that Blinkist could subsequently choose which landing page to use for the global rollout of its promotional campaign. Hence, the experiment did not take place on the venture's official website but on a separate, publicly not visible landing page.

Consistent with the sampling and procedures in previous online experiments (e.g., Ho et al. 2011; Lowry et al. 2013), we recruited participants for the online experiment via e-mail from a representative student subject pool maintained by a large public university in Germany. Subjects were motivated to partake in the study in exchange for a small fee of 2$.

We employed a 2 (scarcity: presence vs. absence) x 2 (social proof: presence vs. absence) between-subjects, full-factorial design. All treatments of scarcity were combined with the social proof treatments on the main campaign landing page, resulting in a total of four experimental conditions (see Figure 12 and Figure 13 for two examples). The landing page

promoted a special offer which allowed participants to secure a 30 day free trial instead of the regular trial that only lasted 3 days. Aside from details about the features of the special offer, the main campaign landing page contained a Learn More button that linked to a video which explained the service, a continue button, as well as a promotional statement and a reference bar (our manipulations) which altered in terms of scarcity (present, absent) and personalization (present, absent) levels (see Figure 12 and Figure 13 for two examples).

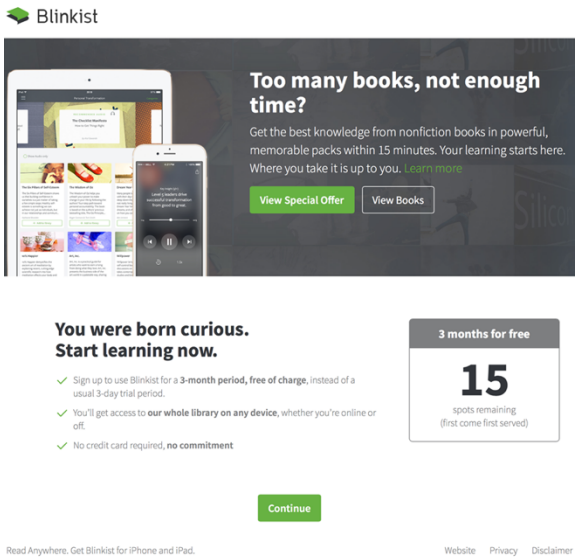


Figure 12. Main Campaign Landing Page (Scarcity, no Social Proof)

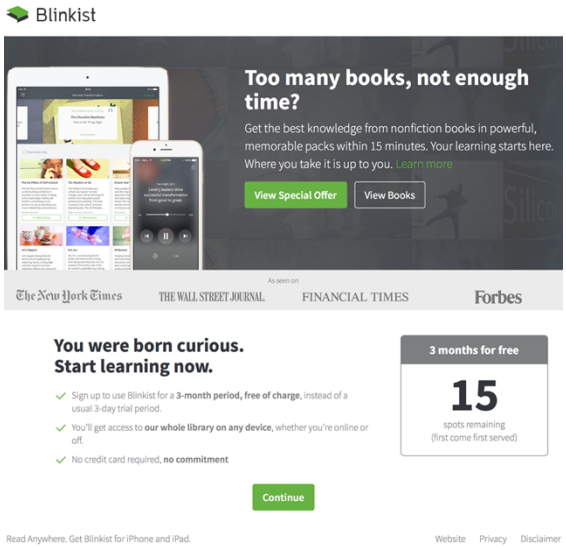


Figure 13. Main Campaign Landing Page (Scarcity, Social Proof)

The experiment proceeded in the following manner: First, participants were given the instruction to look into the promotional campaign of a new online service named Blinkist and to give feedback. They were told to press a “Continue” button on the main campaign website once they were done with reviewing and want to proceed to the feedback step (see Figure 12 and Figure 13). Second, after viewing the instructions, they were forwarded to the main campaign landing page and randomly assigned to one of the four experimental conditions. Here, after pressing the “Continue” button they were provided the opportunity to refer the offer to their friends via a share prompt that, when triggered, gave them the option to log into their Facebook network or enter e-mail addresses of their peers. The purpose of this referral prompt remained obscure throughout the entire experiment and it was not communicated in the instructions at the beginning. Rather, as previously suggest the instructions clearly emphasized the participant’s contribution in providing feedback. Choosing this option led to the direct distribution of Blinkist’s promotional campaign to their peers. After this step, participants were forwarded to a web page containing the post-experimental questionnaire. All participants also had the choice to opt out via a non-share button and were then directly forwarded to the site with the post-experimental questionnaire. In the last step, a post-

experimental questionnaire captured participants responses to questions measuring perceived offer value, control variables, manipulation checks, and several other variables (see Variables Measured and Measurement Validation). Participants were debriefed and thanked for their participants at the end of the survey.

4.4.2 Variables Measured and Measurement Validation

We devised our manipulation for scarcity based on Diab et al. (2008) and Barone and Roy (2010) by restricting the number of spots that were remaining for participating in the offer on a first-come-first-serve basis. This included an unlimited variant (scarcity not present) and a variant that was limited to 15 participants (scarcity present). Scarcity was manipulated in a separate text box on the landing page (see Figure 12 and Figure 13) containing the lines "15 spots remaining (first come first served)". Social proof was implemented as an implicit variant, thereby displaying a "As seen on" bar that listed all media which the venture had been mentioned in (see Figure 13), like it is also common practice in the real world (Kissmetrics.com 2014).

To develop the stimuli for our studies, we conducted a pretest in which 50 participants (48% females, $M_{age} = 26.3$) were randomly assigned to one of the four treatments. The manipulation check of scarcity (present vs. absent) showed that participants perceived the condition containing the scarcity cue as significantly scarcer than the control condition ($F(1, 49) = 52.36$, $p < .001$). Similarly, the manipulation check of social proof (present vs. absent) confirmed that participants had higher demand perceptions when the cue was present than in the control condition ($F(1, 49) = 16.21$, $p < .001$). Furthermore, we also measured consumers' perceptions of demand or popularity in the absence of social proof to ensure that participants perceived scarcity to be based on excess demand rather than supply limitations. The reason for measuring it this way is that social proof is a direct manipulator of perceived demand and we wanted to rule out the cue's effect on demand perceptions when assessing the validity of the demand-based scarcity manipulation. The results suggested that consumers truly perceived the offer in the scarcity condition to be more in demand (more popular) than that in the control condition ($F(1,21) = 7.388$, $p < .05$), therefore confirming that consumers perceived scarcity to be caused by high demand.

Our dependent variable referral propensity was measured binary (referred vs. not referred) in line with (Stein and Ramaseshan 2014) based on actual referral behavior which was collected via clickstream data during the online experiment. Perceived offer value was measured by adapting three items from (Suri et al. 2007).

We chose to measure several control variables that have been identified as the most salient referral drivers in extant literature (i.e., privacy concerns, product involvement need for uniqueness, offer relevance and image-impairment concerns). Information privacy concerns were measured with respect to sharing information online by using three items from Sutanto et al. (2013). Furthermore, product involvement was recorded by adapting one item from Zaichkowsky (1985). Need for uniqueness was measured based on an abridged scale of three items in accordance with Tian et al. (2001). We also quantified information relevance to others to account for differences in participants' perceptions regarding the offer's relevance to theirs peers by adapting one item from Hupfer and Detlor (2006). Lastly, Image-impairment concerns were measured via three items from Argo et al. (2006). A 7-point Likert scale was adopted for all measures with anchors ranging from strongly disagree (1) to strongly agree (7). Information on all constructs and items can be found in Table 10 of the Appendix.

Confirmatory factor analysis (CFA) revealed that all scales exhibited satisfactory levels of convergent validity and each scale's average variance extracted (Awad and Krishnan 2006) exceeded multiple squared correlations, resulting in all discriminant validity requirements being met (Fornell and Larcker 1981). All latent variables were averaged to form composite scores for further statistical analysis as they displayed adequate internal consistency.

Besides rating perceived scarcity (i.e., "The offer that I viewed in the promotional campaign is scarce") and perceived popularity (i.e., "The offer that I viewed in the promotional is redeemed a lot") on a 7-point Likert scale, participants were asked two closed questions in the post-experimental questionnaire: (1) Did you recall seeing a Wall Street Journal, New York Times, Financial Times or Forbes reference when you viewed the main campaign landing page? [Yes or No], and (2) How many free spots were indicated to be remaining when you viewed the campaign landing page? [Unlimited, 50, or 15 spots].

4.5 Results

4.5.1 Sample Description, Control and Manipulation Checks

Out of the 214 subjects from the online pool that were invited to the study, 135 answered our invitation e-mail (response rate: 63%). Seventeen participants (12.6%) were removed from the sample: eight subjects failed to complete the questionnaire and nine moved to quickly through the experiment as indicated by a clickstream analysis and an attention filter question. Hence, we used a sample of 118 subjects in the following analysis, of which 49 were females and 69 males, with average age of 35.99 years, ranging from 19 to 69. Table 7 summarizes the descriptive statistics.

	Mean	StD
Demographics		
Gender (Females)	42%	49%
Age	35.99	11.27
Controls and Mediators		
Product Involvement	4.87	1.45
Privacy Concerns	3.75	1.76
Need for Uniqueness	3.76	1.57
Information Relevance Others	4.95	1.18
Image Impairment Concern	3.87	0.82
Perceived Offer Value	4.79	1.14
Dependent Variable		
Referral %	30%	46%

Notes: means and standard deviations, $N = 118$

Table 7. Descriptive Statistics

We compared both early and late respondents (first and last 50) based on their socio-demographics to rule out a non-response bias (Armstrong and Overton 1977). The results indicated no significant differences between the means of each sample ($p > 0.05$), suggesting that a non-response bias was unlikely to have affected our results. We also believe it is unlikely that our incentives lead to a biased sample selection within the subject pool because the basic demographics (e.g., age, income, gender) between the respondents and the overall pool population were not significantly different ($p > 0.1$).

Furthermore, we conducted several one-way ANOVAs to confirm that the random assignment of participants to the experimental conditions was successful. The results did not indicate any statistically significant difference in product involvement ($F = 0.712$, $p > 0.05$), information relevance to others ($F = 0.848$, $p > 0.05$), privacy concerns ($F = 0.418$, $p > 0.05$), need for uniqueness ($F = 1.002$, $p > 0.05$), image-impairment concerns ($F = 0.424$, $p > 0.05$), age ($F = 1.108$, $p > 0.05$) or gender ($F = 1.148$, $p > 0.05$) between all experimental groups, hence suggesting that randomization was successful. Based on the data provided by Blinkist we were able to verify via clickstream analysis that participants who triggered the share button also actually referred the promotional campaign.

As in the pretest, the manipulation checks indicated that participants rated spots remaining in the scarcity conditions (M = 5.18; SD = 0.96) to be significantly more limited than in the no scarcity conditions (M = 2.91; SD = 1.14) ($F(1,117) = 137.281$, $p < 0.001$). In addition, it could also be confirmed that participants asserted scarcity to be due to high demand rather than limited supply, as the subjects rated the offer in the scarcity condition (M = 4.54; SD =

1.07) to be significantly more popular or in demand than in the control condition in the absence of social proof (M = 3.37; SD = 1.21) ($F(1,117) = 13.806$, $p < 0.001$). Furthermore, the results also indicated that demand or popularity perceptions in the social proof conditions (M = 4.45; SD = 1.35) were significantly higher than in the no social proof conditions (M = 3.94; SD = 1.28) ($F(1,117) = 4.261$, $p < 0.05$). Finally, we determined that all participants passed our tests regarding the two closed manipulation check questions for the four different conditions, implying that the manipulations were successful.

4.5.2 Hypothesis Testing

4.5.2.1 Main Effect Analysis for Scarcity

To test H1, we performed a two stage hierarchical logistic regression on the dependent variable referral propensity (see Table 8). We first entered all controls as well as the mediator perceived offer value (Model 1) and then included the manipulations scarcity and social proof (Model 2). Nagelkerke's R^2 was examined and $\chi 2$-Statistics were computed to analyze the model's significance for both stages. Aside from scarcity and perceived offer value ($p < 0.05$), for which we expected a positive effect on referral propensity, neither social proof nor any of the controls showed a statistically significant direct effect on referral propensity (see Table 8).

The results of the logistical regression demonstrated a statistically significant main effect for scarcity ($b = 1.309$, Wald statistic (1) = 4.614, $p < 0.05$) as well as perceived offer value[8] ($b = 0.651$, Wald statistic (1) = 4.406, $p < 0.05$). Hence, in support of H1, our findings show that participants primed with scarcity are significantly more likely to make a referral than those not primed with scarcity (12% vs. 46%, $t = 18.150$, $p < 0.001$) regardless whether the campaign contained social proof cues or not. This suggests that confronting recipients in a promotional campaign with scarcity significantly increases the likelihood of them referring the offer to their peers.

[8] We interpret the significant mediator perceived offer value when we look at its mediating role between scarcity and consumer referral propensity

	Model 1		Model 2	
	Coefficient	SE	Coefficient	SE
Intercept	-5.038*	2.096	-4.122	2.156
Manipulations				
Scarcity			1.309*	0.610
Social Proof			0.607	0.541
Controls & Mediators				
Gender	-0.039	0.503	-0.538	0.527
Age	-0.005	0.022	-0.010	0.022
Product Involvement	0.047	0.197	0.098	0.206
Privacy Concerns	-0.190	0.143	-0.201	0.146
Need for Uniqueness	0.069	0.150	0.037	0.152
Offer Relevance Others	0.024	0.239	0.117	0.254
Image Impairment Concern	-0.070	0.339	-0.225	0.354
Perceived Offer Value	1.051**	0.270	0.651*	0.310
Log likelihood	115.743		110.349	
Nagelkerke's R^2	0.298		0.348	
Omnibus Model χ^2	27.737**		33.130**	

Notes: * p < .05; ** p < .01; N= 118

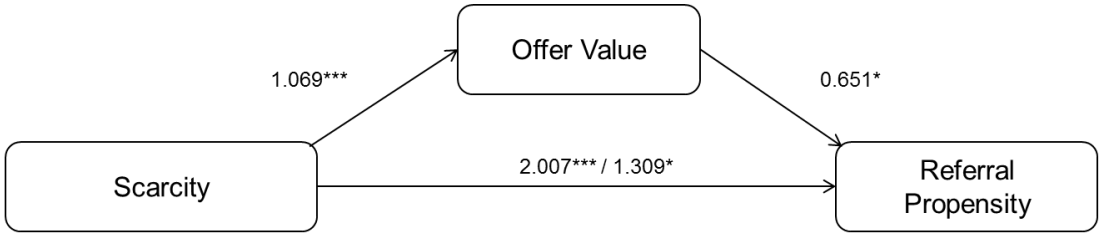
Table 8. Logistical regression on referral propensity

4.5.2.2 Mediation Analysis for Scarcity

In our mediation hypothesis H2, we had argued that scarcity cues' impact on consumers' sharing propensity would be driven by perceptions of offer value. Thus, in a mediation model using bootstrapping with 1,000 samples and a 95% bias-corrected confidence interval, we tested the indirect effect of scarcity on referral propensity through perceived offer value. The mediation analyses was performed using the bootstrap mediation technique (PROCESS macro; Hayes (2013)).

To investigate the process driving the effect of scarcity on referral propensity, we entered perceived offer value as potential mediator between scarcity and referral behavior. The indirect effect of scarcity on referral propensity through perceived offer value was statistically significant (i.e., perceived offer value significantly mediated the relationship: indirect effect = 0.696, standard error = 0.4, 95% bias-corrected confidence interval (CI) = [0.028, 1.494]), supporting H2. Furthermore, scarcity was positively associated with perceived offer value (b = 1.069, p < 0.001), and higher perceptions of offer value were associated with higher probability of making a referral (b = 0.651, p < 0.05; see Figure 14), while scarcity's direct

effect on referral propensity remained significant after perceived offer value was entered into the model, representing the case of a partial mediation (Hayes 2013). Hence, these results showed that perceived offer value significantly mediated the impact of scarcity on referral behavior, such that, as per our proposition, scarcity produced higher perceptions of offer value, which in turn lead to a higher likelihood of referring the promotional campaign.



Note: Coefficients were computed based on mediation analysis using bootstrapping with 1,000 samples and a 95% bias-corrected confidence interval (Hayes 2013); all controls as well as manipulations were included in the analysis; the first coefficient on a given path represents the direct effect without the mediator in the model. The second coefficient represents the direct effect when the mediator is included in the model. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Figure 14. Mediation Results

4.5.2.3 Moderated Mediation Analysis for Scarcity

We hypothesized that the indirect effect of scarcity on referral propensity through perceived offer value is moderated by social proof. Therefore, in accordance with (Hayes 2013), we drew on a moderated mediation model using bootstrapping with 1,000 samples and a 95% bias-corrected confidence interval to test the conditional indirect effect of scarcity on referral propensity through perceived offer value.

The moderated mediation analysis was based on two separate multiple regression models. The first model included scarcity, social proof, the interaction term, and all controls as independent variables and perceived offer value as the dependent variable. This model revealed a positive, statistically significant interaction term ($b = 0.729$, $p < 0.05$), indicating that there was a moderation effect between scarcity and the mediator, therefore supporting H3. As depicted in Hayes (2013, model 7), the predictors in the second model included scarcity, perceived offer value as well as all controls; the dependent variable was referral propensity. This model revealed a significant direct effect of perceived offer value ($b = 0.79$, $p < 0.01$) as well as scarcity ($b = 1.149$, $p < 0.05$) on referral propensity. In addition, Table 9 sheds further light on how the indirect effect of scarcity on referral propensity via perceived offer value was stronger when social proof was present compared to when it was absent.

	Coefficient	Boot SE	BootLLCI	BootULCI
No Social Proof				
Social Proof	30%	30%	30%	46%

Notes: Coefficients were computed based on moderated mediation analysis incl. all controls and using bootstrapping with 1,000 samples and a 95% bias-corrected confidence interval (Hayes 2013)

Table 9. Conditional Indirect Effect of Scarcity on Referral Propensity Contingent on Social Proof

Hence, scarcity, in combination with social proof leads to greater referral propensity due to consumers' higher perceptions of the offer's value (as depicted in Figure 15 and Figure 16). In fact, an ancillary analysis further supported the finding that social proof lead to statistically significant higher offer valuations (4.79 vs. 5.77, $t = 20.77$, $p < 0.001$) as well as referral propensity (31% vs. 57%, $t = 4.34$, $p < 0.05$) when it was incorporated in a promotional campaign containing scarcity. However, it did not demonstrate the same effect on offer valuations ($p > 0.05$) or referral propensity ($p > 0.05$) when scarcity was absent.

Overall, as predicted, these results suggest that participants were more likely to make a referral of a scarce promotional campaign when it contained a social proof cue opposed to when it didn't, because this resulted in even higher offer value perceptions, thus resulting in a higher likelihood of referring the online promotional campaign.

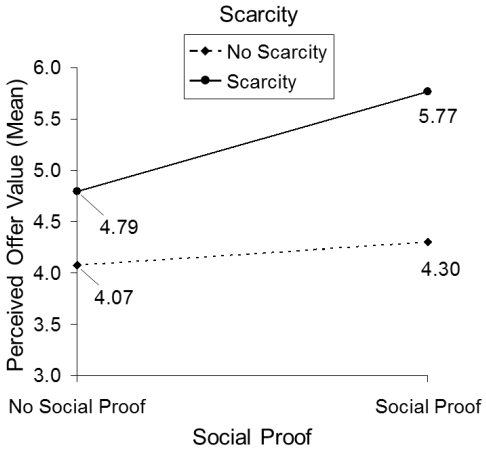


Figure 15. Effect of Social Proof on Perceived Offer Value

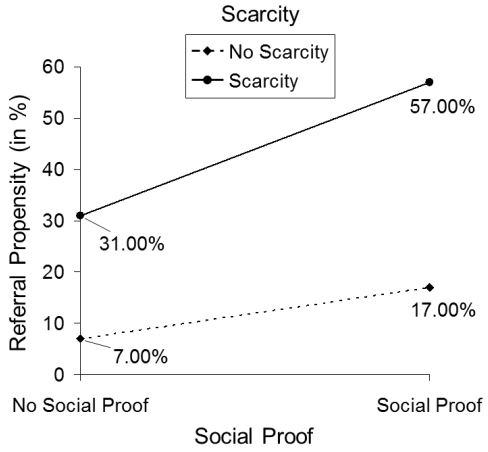


Figure 16. Effect of Social Proof on Referral Propensity

4.6 Discussion

Against the backdrop that firms, and especially IT startups for credibility gains, are increasingly relying on online referrals when generating awareness around their offerings and acquiring new customers, this experimental study aimed to shed light on the potential of

classical promotional tactics in enhancing consumers' referral propensity of online promotional campaigns. We illuminated the potential of scarcity and social proof, as prior research on these promotional cues has demonstrated their influence on factors which are well established drivers of online referral literature and these tactics are often employed in online promotional campaigns together in practice.

Our results support the premise that demand-based scarcity has a positive causal effect on consumers' referral propensity. Moreover, perceived offer value was revealed as partial mediator in the relationship between scarcity and consumer referral likelihood. The underlying theoretical explanation is that consumers may believe to build more social capital when referring a scarcer offer because they perceive the value of the information they are sharing to be greater. Furthermore, the fact that the offer is so limited may also impose direct pressure on consumers to make the referral as fast as possible because the information at hand will become obsolete as time passes. Our mediation results also showed that scarcity's effects were not due to image-impairment concerns, need for uniqueness, privacy concerns, product involvement or offer relevance to others, hence ruling out salient alternative drivers of referral engagement. In addition, we found that social proof acts as significant moderator in the mediating role of perceived offer value. Our results suggest that promotional campaigns including demand-based scarcity cues lead to higher referral likelihood when implicit social proof cues are present compared to when they are absent due to higher offer valuations. We believe this is the case because consumers are likely to attribute great importance to signals that indicate the popularity of the offer (i.e., social proof) as this additional information enables them to make inferences about what the offer's availability was in the past compared to now (i.e., interpretation of relative scarcity) and thus helps them in reducing decision uncertainties.

Our study contributes to ewom literature at the cross-section of IS and marketing in expanding our understanding of the antecedents of ewom behavior in general and online referral behavior in particular. First, we introduce previously underexplored catalysts of consumer referral behavior and provide a validated model through which we illuminate the psychological processes underlying the promotional cues' effects in the context of an online, real world setting measuring actual referral behavior. Second, we analyze two proven promotional tactics from the offline world online. We therefore contribute towards research that deals with the absence of experiential information online by evaluating the effectiveness of signaling mechanisms that may serve as substitutes for some of the information

shortcomings and hence support consumers in their decision making process. Third, we examine how social proof cues, which are popular and are often combined with scarcity in practice, affect the mediating relationship between scarcity and perceived offer value, thereby explicating a moderator for the effect of scarcity on consumer referral propensity. Lastly, our study focuses on referral decisions of first stage actors when initiating viral marketing campaigns, unlike extent research, which has largely placed and emphasis on second stage actors (e.g., De Bruyn and Lilien 2008; Gu et al. 2012). First stage actors have a critical role in creating social contagion because the ability to reach second stage actors is contingent on their referral decisions.

While the preceding paragraph highlighted our theoretical contributions, there are also several practical implications that need to be pointed out. Our findings imply that e-businesses need to employ scarcity cues and if possible supplement these with implicit social proof cues (i.e., signals that manipulate relative demand perceptions like banners indicating what media outlets one has been featured in) when seeking to increase consumer referral likelihood of their online promotional campaigns. In any case, even when social proof is not a viable option, scarcity cues should be incorporated as facilitator of consumer referrals. Furthermore, firms should pay attention to and leverage peoples' need to build social currency in design decisions of their promotional campaigns to drive consumer referral likelihood and therefore the awareness of their offerings.

4.7 Limitations, Future Research and Conclusion

The findings of our study need to be interpreted in light of some noteworthy limitations that also provide avenues for future research. First, caution should be taken when drawing conclusions from one single study. While we chose to conduct our study in a context with broad applicability, we analyzed how scarcity and social proof cues affect referral propensity in the context of e-business and with a special focus on a digital experience good. Future research should examine how these cues work in other business model contexts (e.g., freemium) and for different kinds of goods (e.g., search products). Second, we showed how implicit social proof cues may be used to manipulate prior demand or consumption perceptions when consumers are confronted with a lot of uncertainty, as is often the case with novel offerings. However, for firms that cannot draw on implicit cues (e.g., they have not been featured in the media), explicit social proof cues (e.g., prior purchase counters) may be an effective alternative once a certain purchase threshold is reached. Future studies should examine how best to determine whether and when it may be effective to draw on explicit cues

and how these may influence other important criteria such as firm or offer credibility. Finally, the nature of the study only allowed for observing the influence of the promotional cues on referral decisions of first stage actors. The fact that second stage actors come by a promotional offer through a referral may be interpreted as an additional signal of higher demand and hence further amplify the effects of scarcity on consumer referral propensity. Thus, future research should also pay attention to how scarcity affects referral decisions across different stages of dissemination.

Overall, this study illuminated the potential of promotional cues in enhancing consumer referral likelihood in the context of online promotional campaigns. We contribute towards the understanding of the antecedents of online referrals, which are increasingly being leveraged especially by nascent IT ventures due to credibility gains, when generating awareness around their offerings and acquiring new customers. We hope that our results provide impetus for further analysis of design components that may be leveraged in online promotional campaigns to further increase consumer referral propensity.

4.8 Appendix

Table 10. Measurement Scales

Construct	Item (all 7-Point Likert)
Perceived popularity Van Herpen et al. (2009) (α = 0.86, CR = 0.9, AVE = 0.81)	1. This offer is popular 2. I think that many people want to redeem this offer 3. This offer is redeemed well
Perceived offer value Suri and Monroe (2003) (α = 0.84, CR = 0.87, AVE = 0.73)	1. I think that given this offer's attributes, it is a good value 2. At the advertised conditions, I feel that I am getting a good quality offer 3. If I redeemed this offer at the advertised conditions I feel I would be getting good value
Information privacy concerns Sutanto et al. (2013) (α = 0.82, CR = 0.87, AVE = 0.73)	1. I am concerned with how information about me may be exploited by *Blinkist* 2. I am concerned that my privacy has been compromised by *Blinkist* 3. I am concerned that my personal information may be kept in a non-accurate manner by *Blinkist*
Product involvement Zaichkowsky (1985)	1. I am interested in book summary services like Blinkist
Need for uniqueness Tian et al. (2001) (α = 0.89, CR = 0.92, AVE = 0.81)	1. I collect unusual products as a way of telling people I'm different 2. When products or brands I like become extremely popular I lose interest in them 3. I have sometimes purchased unusual products or brands as a way to create a more distinctive personal image
Information relevance to others Hupfer and Detlor (2006)	1. I believe information about this offer could be relevant to my peers
Image-impairment concerns Zhang et al. (2014) (α = 0.81, CR = 0.85, AVE = 0.73)	1. I feel embarrassed for my buying mistakes 2. Consumers need to worry about how other people view them 3. Looking like a smart shopper is important for me
Perceived Scarcity	1. I think this promotional offer is scarce

5 The Effect of Free Sampling Strategies on Freemium Conversion Rates

Title

The effect of free sampling strategies on freemium conversion rates[9]

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Publication Outlet

Electronic Markets, Online First.

Abstract

Freemium business models, where companies offer a free basic and a value-enhanced paid version of a product, have become ubiquitous across software, games and a broad range of web services. Despite the many benefits of freemium, most firms suffer from too few premium subscribers (3-5%), which challenges their profitability. Although free trials have helped improve premium conversions, research hitherto has paid little attention towards what works effectively. Therefore, we examine the effect of two common free trial strategies on consumers' conversion likelihood: Freefirst, where consumers start in the free and then opt into a trial of the premium version and Premiumfirst, where things are experienced in reverse order. Based on a contest-based online experiment with 225 subjects, our analysis reveals that in contrast to Freefirst, Premiumfirst significantly increases conversion propensity and that this positive effect is greater when the premium and the free version are more similar.

Keywords

Freemium business models; Premium conversion; Free trial strategies; Product value discrepancy; Loss aversion; Randomized online experiment

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5.1 Introduction

The surge of freemium business models across products and services, including software, games, and web services such as Dropbox, Candy Crush or Spotify has brought clear benefits to both users and providers, for example by facilitating the adoption and diffusion of new products. However, the economics of freemium still remain a challenge to companies' profitability (Jiang and Sarkar 2009). Freemium describes business models where firms offer a service or a product for free, but a fee is charged for a premium version that entails advanced features, functionality or less disturbance (i.e., advertising) (Liu et al. 2014). Premium users typically account for 3-5% of total users. Increasing the proportion of premium users opposed to free users continues to be a challenging but critical lever for reaching profitability (Wagner et al. 2014).

Against this backdrop, many firms such as Dropbox or Evernote are using free trials to counter the experience-good characteristics of their digital services and thus attempt to improve premium conversion rates (Dörr et al. 2013; Shapiro and Varian 1998a; Shapiro and Varian 1998b). With experience goods, consumers can only assert various attributes (e.g., value) through direct experience and not via external information (Chiang and Dholakia 2003). In the context of freemium business models, companies offer users a free trial period (e.g., 30 days) to test out the premium offering with the option of going back to the free version after the trial. When adopting free trial strategies, firms commonly implement a *Freefirst* strategy where users would register for a service by starting with a free (i.e., ad-based and/ or feature-limited) version. Only after that they are prompted to try out a time-limited, feature-enhanced premium version for free they are required to make a subscription decision. More recently, however, firms such as Blankcanvas.io are adopting a *Premiumfirst* strategy for their products. Here, users start off with a time-limited, ad-free and fully featured free-trial of the premium version upon registration and then are downgraded to the free (i.e., ad-based and/or feature-limited) version before making an active, informed subscription decision. The basic idea of this strategy is that it may result in more users making an active, informed subscription decision instead of sticking to the free version without really understanding what the premium version is all about. Furthermore, based on the notion of loss aversion, which describes a cognitive misperception that refers to the psychological anomaly where consumers perceive the disutility of giving something up to be greater than the utility associated with acquiring it (i.e., "losses loom larger than gains") (Kahneman et al. 1991; Kahneman and Tversky 1979), *Premiumfirst* may have a positive effect on how consumers perceive the added value of the premium compared to the free version and thus affects

conversion rates.

Previous research has investigated the overall benefits of freemium business models (e.g.,Jiang and Sarkar 2009; Kumar 2014; Liu et al. 2014) and has emphasized product value discrepancy between the free and premium versions (i.e., the value differential perceived by users in terms of functionality and user experience) as critical driver of premium conversion decisions (e.g., Wagner et al. 2014). However, although the benefits of free trials in the context of information-related experience-goods is widely acknowledged (e.g., Lee and Tan 2013; Shapiro and Varian 1998a; Shapiro and Varian 1998b), minimal attention has been directed towards examining the differential effects of free trial strategies (i.e., *Premiumfirst* vs. *Freefirst*) and their interaction with varying levels of product value discrepancy between the free and premium versions in the context of freemium business models. To address these research gaps, this study aims at shedding light on the following two research questions:

(1) What is the effect of Premiumfirst opposed to Freefirst in affecting conversion rates?

(2) What is the effect of Premiumfirst opposed to Freefirst in affecting conversion rates for different magnitudes of product value discrepancy between the free and the premium version?

This paper sheds light on the differential effects of *Premiumfirst* and *Freefirst* strategies on premium conversions as well as the role of perceived product value discrepancy between the free and premium version in moderating this effect by drawing on a contest-based online experiment with 225 subjects. Our study aims at gaining new insights into the conversion process of freemium users to derive implications for the design of freemium business models.

The rest of the paper is organized as follows. In the next sections, we review prior literature on freemium as well as behavioral economics, specifically the concept of loss aversion, and present our research model and hypotheses. The subsequent section describes the research methodology used within our experimental study, followed by our data analysis and the results of hypothesis testing. Finally, we discuss our findings, limitations, implications and directions for further research. The last section concludes our paper.

5.2 Background

5.2.1 The Freemium Business Model

In freemium business models, companies offer a free basic and a value-enhanced paid version of a product (Veit et al. 2014). The music streaming service Spotify for example offers a free version where users can access unlimited songs as long as they are connected to the internet

and are willing to bear disturbing audio ads which cannot be skipped (Wagner et al. 2014). In the paid premium version, users are not only spared from the disturbing ads, but they may also access their songs offline from anywhere.

Firms drawing on freemium believe that offering a free basic version is an effective way to attract new users and to build a brand. Many practitioners claim that a great proportion of users that end up purchasing the premium version would not have done so without the free version in place (Lee and Tan 2013; Liu et al. 2014). Furthermore, when paired with social sharing incentives like paying users for every new user that they bring, free users become an effective lever for rapidly growing a company's user base (Benlian 2015b; Lee et al. 2013). In the context of mobile applications, even when such incentives are absent, a free app that makes it to the top of an app store's ranking list can improve the visibility of the product because it will be displayed on the main page, therefore creating a virtuous loop that leads to more free users, which in turn can boost sales of the premium version (Liu et al. 2014). Free users are also particularly valuable to businesses which operate in markets where so-called same-side network effects are at play, meaning situations where more users increase the value of the product or service for any given users (Cheng and Tang 2010). This is for example the case with Skype, where the product's value to users is greater when they can reach more people.

Freemium has been adopted by many established companies as well as nascent ventures ranging from Freemail providers like Yahoo, telecommunication providers like Skype over Music as a Service providers like Spotify to cloud storage providers like Dropbox. The common denominator between these companies is that they rely on revenues coming from their comparatively small base of paying premium users (3-5%) to finance non-paying free users, while it has also become common to draw on advertisement in the free version as additional stream of revenue. Whereas the marginal cost of free users in social networks or online games is almost zero, it is often very costly to maintain them in other contexts such as in the case of music services, where royalties have to be paid or in cloud storage services where storage has to be held. Under such circumstances, payments from premium users often in combination with advertising revenues through free users are not necessarily sufficient to subsidize the free version (Wagner et al. 2014). Therefore, firms operating in freemium business models aim at maximizing the total amount of premium users by reaping the advertising benefits obtained through free users while minimizing the costs associated with these and simultaneously encouraging as many as possible to subscribe to the premium

version.

Aside from having identified many benefits of the freemium business model, extant research has also paid attention to factors which drive premium conversion rates, especially the product value discrepancy between the premium and free version (also called *premium fit*) (Lee et al. 2013; Wagner et al. 2014). Value discrepancy describes the extent to which the free version differs from the premium version. The magnitude of this value discrepancy is critical in persuading users to switch from free to premium (Wagner et al. 2014). The suggestion is that the greater the value contrast between the two versions, the higher the proportion of premium users will be, particularly because the incremental value of premium is perceived to be higher. Therefore, a product where the free version has very few features compared to the full (commercial) product creates high value discrepancy. On the other hand, a product where the free version contains many features that the full (commercial) product has creates low value discrepancy.

Firms employ different magnitudes of differentiation to steer perceptions of value discrepancy. Dropbox for example offers users two gigabytes of online storage space for free; paying customers can use up to 1 terabyte. In the case of Spotify, free users can listen to music for free, however, with advertising interruptions which are absent in the premium version. Over time the firm has continuously increased the contrast between the free and premium version by adding advanced features such as an offline listening mode for premium users, which demonstrates that companies also change their strategy throughout a product's lifecycle (Kumar 2014). The reason for the large differences in value discrepancy across businesses and changes of value discrepancy even throughout a product's life cycle lies in the inevitable balance that companies need to strike between the advertising effect of free and higher premium subscription rates. On the one hand, low value discrepancy, optionally combined with social sharing incentives, favors the generation of traffic and hence attracts new users, as it is more appealing when a product or service is free (Kumar 2014). On the other hand, a high value discrepancy is likely to increase users' motivation to subscribe to the premium version due to relatively greater limitations of the free version in functionality or user experience and thus to greater differences in perceived value between the premium and free version (Wagner et al. 2014). Thus, companies are confronted with a dilemma and may need to tweak product value discrepancy throughout different stages of a product's life cycle to realign it with their objectives.

More recently, attention has shifted towards freemium providers such as Dropbox and

Evernote that have started to adopt traditional free trial strategies to overcome the experience-good character of the premium version. Firms typically draw on a *Freefirst* strategy where users start by registering for the free version of a product or service. At this time, the main objective of the provider becomes to convince users that they need the premium version because it offers advanced features, no advertising or other benefits. To lower these entry barriers and especially influence users' risk perceptions, a time-limited free trial of the premium version is offered. One rather critical issue with this undertaking is that many users may actually ignore the provider's messages or simply are not convinced or motivated enough to try out the premium version. Those that do try out the premium version come to decide at the end of the trial phase whether to continue with the premium version by subscribing or they may simply revert back to the free version. A hitherto under-studied but increasingly used alternative, which has been noticed and implemented by companies such as Blankcanvas.io, is called *Premiumfirst*, where users opt into a time-limited free trial of the ad-free and fully-featured premium version when they register and are then moved into an ad-based and/or feature-limited free version when the trial period ends. This results in more users making an active, informed decision whether to remain in the free version or subscribe to premium. However, the fact that the total number of users that will have examined the premium version in *Premiumfirst* is higher than in the *Freefirst* model also raises the question how users' decision to convert to premium is affected in the post-trial phase (i.e., after they have experienced the premium version in the trial phase). More specifically, one would be interested in understanding how *Premiumfirst* performs compared to the more traditional method in terms of users' decisions to subscribe to premium once they have actually tried the premium version. The concept of loss aversion from behavioural economics serves well in providing a potential explanation on how the different strategies may affect consumers' value perceptions and hence their conversion decision.

To the best of our knowledge, extant research has paid little attention towards the effectiveness of different free trial strategies (*Freefirst* vs. *Premiumfirst*) in the context of freemium business models. As yet, the focus has been on the effective- ness of free trial strategies in the context of information products in general (Shapiro and Varian 1998a; Shapiro and Varian 1998b) and therefore neglects the complexity of freemium business models where users may opt into the free version of the product instead of only choosing between a purchase or not. We therefore intend to close this gap.

5.2.2 The Concept of Loss Aversion

Classical decision making models imply that consumer decisions do not depend on current assets (Novemsky and Kahneman 2005). However, contemporary research and specifically the phenomenon of loss aversion propose evidence that individual choice does indeed depend on current holdings (Tversky and Kahneman 1991). Loss aversion describes a cognitive misperception that refers to the psychological anomaly where consumers perceive the disutility of giving something up to be greater than the utility associated with acquiring it (i.e., "losses loom larger than gains") (Kahneman et al. 1991; Kahneman and Tversky 1979). This discrepancy is often also referred to as the endowment effect. Reference dependence is a fundamental characteristic to this phenomenon and it implies that losses loom larger than gains relative to a current endowment (Ariely et al. 2005).

Although there has been plenty of research on the phenomenon of loss aversion and its influence on consumers' value perceptions in situations of certainty (e.g., Tversky and Kahneman 1991) and uncertainty (e.g., Novemsky and Kahneman 2005), to the best of our knowledge, there has been little research on how this phenomenon may be leveraged to influence consumer conversion decisions in the context of freemium business models.

5.3 Research model

5.3.1 The Effect of Free Trial Order on Consumer Conversion Propensity

Literature describes loss aversion as a phenomenon where, based on a specific reference point, consumers will perceive the disutility of giving something up to be greater than the utility associated with acquiring it (Kahneman et al. 1990). Loss aversion may significantly influence consumer decision making (Kahneman et al. 1991; Kahneman and Tversky 1979). We propose that leveraging loss aversion by implementing a *Premiumfirst* opposed to a *Freefirst* strategy in the context of freemium business models will lead to an increase in consumers' conversion propensity after they have gone through the trial phase.

Practitioners of freemium business models draw on free trials to reduce consumer uncertainties regarding the benefits and incremental value of the premium version with the ultimate goal of positively influencing their conversion decisions (Shapiro and Varian 1998a; Shapiro and Varian 1998b). The providers may choose between a *Premiumfirst* and the more traditional *Freefirst* strategy. Although consumers are ultimately confronted with the same decision after the trial in both methods (i.e., convert to premium or stick to the free version), their reference points will differ sharply. In *Premiumfirst*, users will have started and learned to value the functionality of the premium version. Therefore, when switching to the free

version afterwards, they likely use the premium version as reference point in assessing the value of the free version. On the other hand, in *Freefirst, users start with a free version missing features that are available in the premium version.* Therefore, when switching to the premium version afterwards, they are likely to use the free version as reference point for assessing the value of the premium version.

In sum, based on the notion of loss aversion, we expect that the perceived disutility is higher when consumers' reference point is the premium version and they are moved to the free version at the end of the trial (i.e., *Premiumfirst*) than the utility gained when they commence in the free version and then are moved to the premium version (i.e., *Freefirst*). We argue that this endowment effect will differentially influence consumers' conversion decisions. In other words, we expect that consumers will perceive the incremental value of the premium over the free version as higher in the *Premiumfirst* opposed to the *Freefirst* model due to the effects of loss aversion, which in turn will increase their conversion propensity. Hence, we expect that

H1. Consumers will be more likely to make the decision to convert to the premium version when undergoing a *Premiumfirst* compared to a *Freefirst* strategy.

5.3.2 The Moderating Role of Product Value Discrepancy

H1 proposes that *Premiumfirst* encourages post-trial consumer conversions due to the effects of loss aversion. However, as previous research points out, firms may choose to adapt the value discrepancy between the free and premium version depending on the product's lifecycle and other reasons (Kumar 2014), which in turn affects consumers' value perceptions and conversion decisions. This bears the question how *Premiumfirst* opposed to *Freefirst* strategies affect consumer conversion decisions at different levels of product value discrepancy.

We propose that low opposed to high perceived value discrepancy between the free and the premium version increases the positive effect of *Premiumfirst* on consumers' conversion propensity. We believe this is the case because high value discrepancy cancels out the effect of loss aversion on conversion rates as a high value differential will likely be such a dominant and evident driver for their conversion decision that any loss aversion considerations will be pushed to the sidelines. That is, users will go for the premium version either way because the value difference is so prominent and consequential. On the other hand, when discrepancy is low, the effect of the difference between free and premium takes a back seat in users' decision-making so that loss aversion affects conversion propensity. Take a web-based email

provider as an example. If the premium version had let's say 15 GB of storage and the free version only had 50 MB (an example of high value discrepancy), then the difference in storage space utility between the two versions is so prominent that it does not really matter whether consumers undergo *Premiumfirst* or *Freefirst*. If on the other hand the premium and free version had the same or similar storage space and the only difference were a 10s non-blockable ad overlay that is displayed in regular intervals throughout a session (e.g., every five minutes), the value discrepancy between the two versions is so minor that when users start off with the premium and then move to the free version, the pain is likely perceived to be much greater than the gain when moving from free to premium. This discrepancy in perceived loss and perceived gain could thus be explained through the effect of loss aversion. Figure 17 provides a summary of our research model and hypotheses.

Overall, we thus suggest that choosing a *Premiumfirst* opposed to a *Freefirst* strategy leads to a larger improvement in conversion likelihood when value discrepancy is low compared to when it is high. Therefore, we hypothesize that.

H2. Product value discrepancy will moderate the relationship between free trial strategy and consumer conversion propensity such that *Premiumfirst's* effect on consumer conversion propensity will be higher when product value discrepancy is low compared to high.

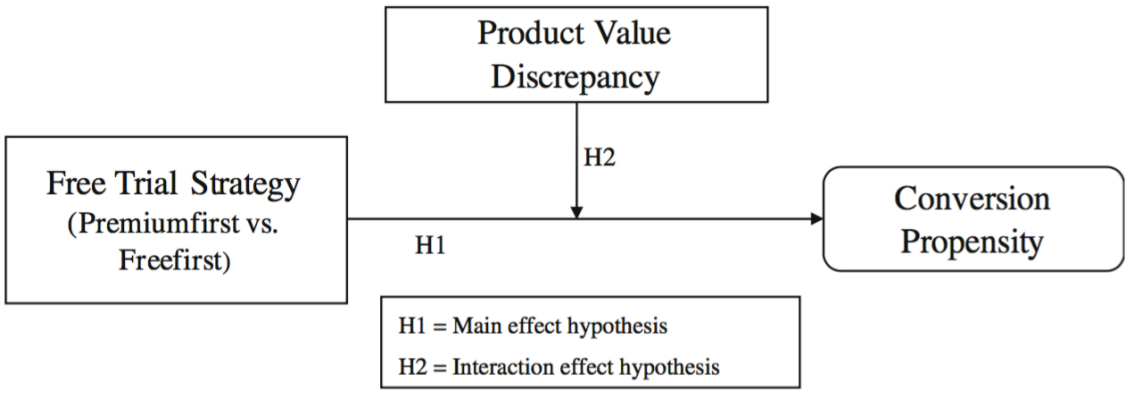

Figure 17. Research Model and Hypotheses

5.4 Research Methodology

5.4.1 Experimental Design and Procedures

We conducted a contest-based online experiment to test our hypotheses. The study was positioned as preparatory measure in the context of an online contest where users had the chance of winning $10 based on the number of math problems they solved (correctly) within a given period. The preparatory measure gave users the chance to test a free and premium

online calculator called iCalculator by solving various math problems before making a decision whether they would compete with the free or premium version within the actual contest. The iCalculator was self-developed by the authors and designed according to real online calculator services offered through a freemium business model on the Internet. In their basic and free versions, such online calculators offer only basic features and display ads from third-party companies, while the premium versions are ad-free and contain much more features and add-on functionalities such as graphical plotting functions which are comparable to that of an advanced physical calculator (such as the TI86 from Texas Instruments).

In our experimental study, we employed a 2 (Free Trial Strategy: *Freefirst* vs. *Premiumfirst*) × 2 (Product Value Discrepancy: Low vs. High) between-subjects, full-factorial design {Benlian, 2015 #231}. Aside from manipulating the order in which the users experienced the premium and free version, which led to the two different free trial strategy conditions (*Premiumfirst* vs. *Freefirst*), we also manipulated the level of product value discrepancy in the two different conditions (low vs. high).

Consistent with the sampling and procedures in previous online experiments (e.g., Ho et al. 2011; Lowry et al. 2013), we recruited participants for the online experiment via e-mail from a representative student subject pool maintained by a large public university in Germany. Subjects were motivated to partake in the study in exchange for a small fix reward of €2. Those who opted to participate could click a web link in the email to start the process. As depicted in Figure 18, the experiment proceeded in three major steps. First, before being randomly assigned to one of the four conditions, participants received the instructions that they will be getting access to both the free basic and a paid premium version of an online calculator called iCalculator and that they will be asked to answer some questions while doing so. They were also informed that after having tested the two versions they would proceed to the actual contest where the math problems will be similar to those that they will receive while testing the two different calculator versions. They then commenced in one of the four experimental conditions and tried to solve as many math problems as possible with the provided calculator version in a time frame of 2 min (Step 1). Second, they were forwarded to the other version of the calculator (i.e., either premium of free depending on the condition they were assigned to) and again solved math problems for 2 min (Step 2). In the last step of the experiment, participants were forwarded to a questionnaire that recorded demographics, risk attitudes and other variables, after being confronted with the decision what calculator to use (Step 3) in the upcoming math contest (Step 4). They had the choice of proceeding with

the free version or sacrificing €5 out of their potential €10 prize for being able to compete with the premium version of iCalculator. This decision represents a trade-off to the users in terms of forfeiting a proportion of their potential gains for a better chance of winning depending on their perceptions regarding the incremental value of the premium version and is a common incentivization in contest-based online experiments (Bardsley 2010). At the end, subjects were debriefed and thanked for their participation.

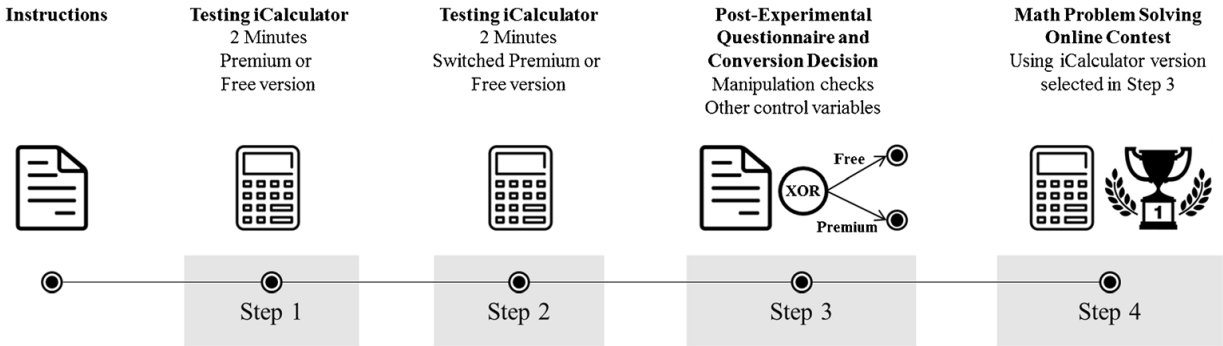

Figure 18. Experimental Procedure

5.4.2 Manipulations and Measured Variables

The two free trial strategies were implemented as follows: in *Freefirst*, users started with the free version and switched to the premium version after 2 min (see conditions 1 & 3 in Table 11). In the *Premiumfirst* condition, users started with the premium version and then were moved to the free version after two minutes (see conditions 2 & 4 in Table 11). Product value discrepancy was manipulated by adding or removing features to/from the premium/free version (see conditions 1 & 2 – low discrepancy vs. 3 & 4 – high discrepancy in Table 11). More specifically, in the low value discrepancy condition, the only factor that the premium version differed in was the absence of an 8s ad which was displayed after every solved math problem. In the high value discrepancy condition, the premium version also had more task-relevant features (e.g., exponentiation functions) aside from the absence of ads. In total, as depicted in Table 11, our experiment consisted of four conditions by combining each of the two free trial strategies (*Premiumfirst* vs. *Freefirst*) with the two levels of value discrepancy (low vs. high).

Conditions:	1. Freefirst-Low Discrepancy		2. Premiumfirst-Low Discrepancy	
Order of Free Trial Strategies:	Step 1: Free version	Step 2: Premium version	Step 1: Premium version	Step 2: Free version
Value discrepancy manipulations:	Basic calculator features with ads*	Basic calculator features without ads	Basic calculator features without ads	Basic calculator features with ads
Conditions:	3. Freefirst-High Discrepancy		4. Premiumfirst-High Discrepancy	
Order of Free Trial Strategies:	Step 1: Free version	Step 2: Premium version	Step 1: Premium version	Step 2: Free version
Value discrepancy manipulations:	Basic calculator features with ads	Advanced calculator features** without ads	Advanced calculator features without ads	Basic calculator features with ads
Note: * Ads include 8 seconds ads after each solved math problem displayed right next to the calculator ** Advanced features include additional calculator features (e.g., exponentiation or square roots functions) available to users that facilitate calculation procedures for solving math problems				

Table 11. Four Experimental Conditions (Between-Subjects)

To develop the stimuli for our studies and serving as preliminary manipulation checks, we conducted a pre-test in which 35 participants (52 % females, mean age = 24) answered closed manipulation questions regarding the free trial strategy and assessed the value discrepancy between the free and premium version. For the free trial strategy, all participants rated the order in which they experienced the premium and free version correctly. Furthermore, they also assessed the value discrepancy in the high discrepancy condition to be significantly greater (M = 5.89) than in the low discrepancy condition (M = 4.24) ($F(1, 34) = 30.92$, $p < .001$).

Our dependent variable (i.e., propensity to convert), was measured as a binary variable (converted vs. not converted) based on actual conversion during the online experiment. In consonance with Moe and Fader (2004), who measured purchase propensity in the context of website visits, we describe conversion propensity as the probability of making a conversion by defining a point estimator based on:

$$P\ (\text{conversion}\ in\ Group\ Z) = \frac{\sum_{k=1}^{n} x_k}{n}$$

Where Z refers to one of the four subgroups or conditions (e.g., *Premiumfirst* & Low Value Discrepancy), n denotes the total amount of participants in the respective subgroup and x_k is a dichotomous variable which equals 1 when a participant decided to convert and 0 if not.

In addition, the following control variables were measured: age, gender, education (years of schooling), risk aversion and performance differential within the experiment. Risk aversion was measured according to the decision-based scenario of Kahneman and Tversky (1979) in

which consumers have to decide between a sure $5 payoff and an uncertain $10 payoff with a 50 % probability. Performance differential was measured as the difference in points scored in the premium version vs. the free version, whereas points are calculated through the amount of problems solved and the percentage solved correctly. We checked the identification of the free and premium version based on the sequence they were accessible during the testing steps via a manipulation check question (i.e., "In what order did you have access to the full and limited version of iCalculator? (1) Step 1: Full; Step 2: Limited or (2) Step 1: Limited; Step 2: Full"). Perceived product value discrepancy was measured through a manipulation check question (i.e., "The free version differentiates strongly from the premium version") in accordance with Wagner et al. (2014). A 7-point Likert scale was employed here with anchors ranging from strongly disagree (1) to strongly agree (7).

5.4.3 Sample Description, Control and Manipulation Checks

Out of the 325 subjects from the online pool that were invited to the study, 240 answered our invitation e-mail (response rate: 74 %). Fifteen participants were removed from the sample because they failed to complete the questionnaire and failed the attention filter question. Hence, we used a sample of 225 subjects in the following analysis, of which 100 were females and 115 males, with an average age of 24.09 years, ranging from 19 to 42. Table 12 summarizes the descriptive statistics including all dependent variable cell means, which are interpreted in the Interaction Effect Analysis for Free Trial Order and Product Value Discrepancy section.

We tested for a non-response bias by comparing the answers of the last quarter of participants with the answers of the remaining participants (Armstrong and Overton 1977; Lambert and Harrington 1990). The results showed no significant differences such that non-response bias is unlikely to have affected the results of this study. Furthermore, we conducted several one-way ANOVAs to confirm that the random assignment of participants to the experimental conditions was successful. The results did not indicate any statistically significant differences in age, gender, education and risk attitude between all experimental groups, hence suggesting that randomization was successful (all $p > .05$). As in our pre-test, all participants rated the order of the premium and free versions to which they were assigned correctly. Furthermore, they also assessed the value discrepancy in the high discrepancy condition to be significantly greater (M = 5.84) than in the low discrepancy condition (M = 3.71) ($F(1, 216) = 26.3$, $p < .001$). Consequently, our manipulation checks proved successful.

Although our study focuses on the results obtained from a product evaluation and not the actual contest and users therefore had little motivation to cheat, we measured various metrics to ensure that participants complied with the rules of the experiment (i.e., not to use a calculator other than iCalculator when solving the tasks). Aside from the average time required to solve a task and the number of tasks solved in the 2 min timeframe, we also measured the number of buttons pushed (i.e., operations and numbers) on iCalculator. We did not identify significant deviations, suggesting that participants were unlikely to have used a third-party calculator.

	Mean	StD	Min	Max
Demographics				
Age	24.09	2.37	19	42
Controls				
Risk aversion	0.24	0.43	0	1
Performance differential	2.23	1.63	0	8
Dependent Variable				
Overall Conversion (in %)				
Conversion % freefirst low discrepancy	86.00%	0.35	0	1
Conversion % premiumfirst low discrepancy	50.00%	0.51	0	1
Conversion % freefirst high discrepancy	91.00%	0.29	0	1
Conversion % premiumfirst high discrepancy	90.00%	0.30	0	1

Notes: means, standard deviations and range, N = 217

Table 12. Descriptive Statistics

5.5 Results

5.5.1 The Effect of Free Trial Order on Consumer Conversion Propensity

To test H1 and H2, we conducted a two stage hierarchical logistic regression on the dependent variable conversion propensity (see Table 13) (Hayes 2013). We first entered the main effects (Model 1) and then the interaction effect (Model 2). Both models were statistically significant at $p < 0.001$. We excluded the controls from our analyses because they did not significantly differ between the experimental conditions. Furthermore, there were also no significant correlations among the controls and between the controls and the dependent variable.

The results of the logistical regression revealed a significant main effect of free trial order ($b = 1.801$, Wald statistic (1) = 16.681, $p < 0.001$) and value discrepancy ($b = 1.770$, Wald statistic (1) = 18.424, $p < 0.001$). Hence, consistent with H1, the odds ratio suggests that the odds of converting in *Premiumfirst* are 6.053 times the odds of converting in *Freefirst*.

Furthermore, consistent with the findings of Wagner et al. (2014), participants in the high discrepancy condition were 5.868 times more likely to convert to the premium version than those in the low discrepancy condition. Taken together, these results show that priming users in a freemium business model with a *Premiumfirst* strategy significantly increases the probability of them converting.

	Model 1			Model 2		
	Coefficient	SE	Odds ratio	Coefficient	SE	Odds ratio
Intercept	0.138	0.260	1.147	0.00	0.267	0.000
Manipulations						
Free Trial Strategy[1] (base case Freefirst)	1.801***	0.441	6.053	2.303***	0.540	10.00
Value Discrepancy[2] (base case low value discrepancy)	1.770***	0.412	5.868	2.181***	0.480	8.857
Free Trial Strategy X Value Discrepancy				-1.845*	0.899	0.158
Log likelihood	182.309			178.485		
Nagelkerke's R^2	0.245			0.268		
Omnibus Model χ^2	37.214***			41.038***		

Notes: * p < .05; ** p < .01; *** p < .001, N = 217
[1] Free trial strategy was dummy coded with 0 = Freefirst and 1 = Premiumfirst
[2] Value Discrepancy was dummy coded with 0 = Low Discrepancy and 1 = High Discrepancy

Table 13. Binary Logistic Regression

5.5.2 Interaction Effect Analysis for Free Trial Order and Product Value Discrepancy

As indicated in model 2 of our logistic regression results (see Table 13), the main effects of Free Trial Strategy and Value Discrepancy on conversion propensity were qualified by a significant two-way interaction ($b = -1.845$, Wald statistic (1) = 4.214, $p < 0.05$), suggesting that both main effects on conversion behavior are contingent on the presence of each other. To further test H2, we conducted planned contrast comparisons to examine the conditional effects of Free Trial Strategy at different levels of Product Value Discrepancy (low, high). The results in Figure 19 highlight that when value discrepancy is low, participants are more likely to convert to premium in the *Premiumfirst* opposed to *Freefirst* strategy (91.00 % vs. 50.00 %, $F = 27.293$, $p < 0.001$). However, a significant difference in conversion propensity between *Premiumfirst* and *Freefirst* did not emerge at high value discrepancy (93.00 % vs. 90.00 %, $F = 0.406$, $p > 0.25$).

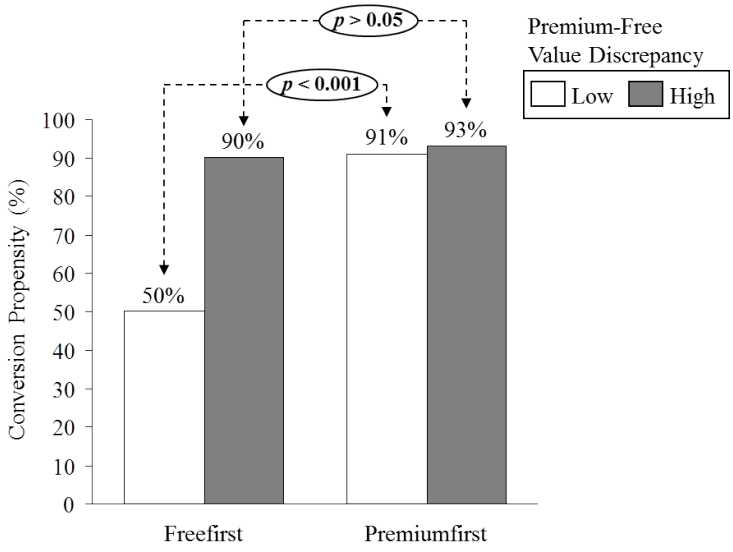

Figure 19. Conversion Propensities for Premiumfirst vs. Freefirst at Low vs. High Levels of Value Discrepancy

5.6 Discussion

This paper aimed to shed light on the potential of *free trial strategies* in improving consumers' premium conversion propensity within freemium business models.

Our results support the premise that *Premiumfirst* has a positive causal effect on consumers' conversion propensity. The underlying theoretical explanation is that consumers will perceive the incremental value of the premium over the free version as higher in the Premiumfirst opposed to the *Freefirst* model due to the effects of loss aversion, which in turn will increase their conversion propensity. In addition, we found that product value discrepancy acts as significant moderator for the effect of *Premiumfirst* on consumers' conversion propensity. Our results suggest that *Premiumfist* leads to a higher increase in conversion likelihood when value discrepancy is low compared to when it is high. We believe this is the case because high value discrepancy cancels out the effect of loss aversion on conversion rates as it is the more dominant driver (i.e., users will go for the premium version either way because the value discrepancy is so prominent). On the other hand, when value discrepancy is low, the effect of the difference between free and premium takes a back seat so that loss aversion becomes the more dominant mechanism affecting conversion propensity.

Our study contributes to the still nascent freemium literature and research on free trial strategies by expanding our understanding of the antecedents of consumer conversion decisions in freemium business models. We examine a previously underexplored free trial strategy, *PremiumFirst*, and its impact on conversion behavior in the context of an online

experiment measuring actual conversion behavior. Furthermore, we examine how the level of product value discrepancy, which has represented a big dilemma in terms of trading off the positive effects of free and the cost of giving up premium conversions, affects the relationship between *Premiumfirst* and conversion propensity, thereby explicating an important moderator for the effect of the *Premiumfirst* strategy.

While the preceding paragraph highlighted our theoretical contributions, there are also several practical implications that need to be pointed out. Although our results may lead to conclude that firms should always employ *Premiumfirst*, we believe *Premiumfirst* is by no means a panacea and that one needs to interpret our findings with caution. Premiumfirst should rather be considered as additional option in the strategic arsenal of design choices. Especially for firms which follow a strategy of high value discrepancy due to cost dynamics (i.e., the costs generated by free users are high), *Premiumfirst* may not always be the most attractive option. In such situations, placing every user in a time-limited premium trial from the very start equates to a large upfront investment that may never be recouped. The company may very well be better off just trying to upgrade selective users by offering time-limited trials based on what is affordable. However, we do urge firms that employ financially viable low discrepancy strategies to consider *Premiumfirst* as effective alternative to the more common choice of *Freefirst* because it allows benefiting from advertising effects without sacrificing premium conversion rates.

The findings of our study need to be interpreted in light of some noteworthy limitations that also provide avenues for future research. We provided loss aversion as plausible explanation for the effect of *Premiumfirst* on conversion propensity. Another related theoretical lens that may explain our results is the status quo bias, which claims that humans simply resist change. More research is required to identify what is actually driving the positive effect of *Premiumfirst*. Also, our study has focused only on one moderating mechanism (i.e., value discrepancy). Future studies need to consider other possible moderators. Distraction due to ads may hinder users from coming up with a perceived value differential between the free and premium version. Also, the value differential may for example be driven by how complete users perceive the free version to be. Furthermore, caution should be taken when drawing conclusions from one single and cross-sectional study. Due to the nature of the experimental setting, we were not able to examine the effects over a longer time frame. Consumers often enjoy a 30-day trial period before making a conversion decision. Future research should examine our findings across other contexts (e.g., entertainment/ video on demand services)

and at various trial phase lengths. Lastly, even though we believe our subject pool is representative for typical consumer behaviour, it does represent a limitation. Future studies should focus on corroborating our findings in the context of randomized field experiments with actual consumers.

In conclusion, this study illuminated the interaction between different free trial strategies and product value discrepancy in enhancing consumer conversion likelihood in the context of freemium business models. This interplay is critical for freemium business models, which are increasingly being adopted especially because of the benefits related to rapid product adoption and diffusion, yet are still challenging when it comes to reaching profitability due to low premium conversion rates. We hope that our study gives fresh impetus to fuel the stream of research on (freemium) business models and also help online firms to refine their knowledge about how they can shape free trial strategies and product value discrepancy to affect premium conversion of their customers.

6 Thesis Conclusion and Contributions

Advances in technology, specifically the rise of the internet, have enabled digital business models that have disrupted entire industries (Bharadwaj et al. 2013). While the impact of digitalization on value creation is quite well understood and continues to garner attention from research, a lot of questions remain with regards to how to capture the value that is being created. More specifically, competition in the online space is fierce, so in order to win new customers, firms are required to rethink the design of their conversion funnel (Porter and Golan 2006; Teece 2010). This thesis is motivated by the the need for a better understanding of how to shape the conversion funnel of digital business models to drive better acquisition and conversion outcomes, specifically by drawing on digital nudges. Against this backdrop, three studies were conducted. Sections 6.1 and 6.2 summarize and discuss the main theoretical and practical contributions of these studies.

6.1 Theoretical Contributions

Overall, this thesis contributes towards IS and marketing by enhancing our understanding of digital nudges as well as the conversion funnel of digital business models. As the studies we conducted refer to two different parts of the conversion funnel (i.e., acquisition and customer conversion), the main contributions to each part of the funnel will be presented separately.

Through the first two studies, we were able to advance our understanding of how digital nudges may enhance acquisitions. More specifically, we provide evidence of how digital nudges may be used to increase consumers' propensity to engage in referrals, which are considered to be one of the most cost effective and successful acquisition methods (Godes and Mayzlin 2004). We found that both scarcity and personalization nudges may positively enhance referrals of online promotional campaigns, although they do this through different psychological processes. Furthermore, we show that there is an interaction between these two nudges that leads scarcity to override the positive effects of personalization. We argue that this is the result of scarcity nudges causing a progressive decrease in information processing and thus undermining personalization nudges to trigger the psychological processes through which they affect consumer decision making. Our second study expands on those findings by showing that scarcity and social proof nudges lead to a completely different interaction effect which is characterized by amplification (i.e., social proof enhances scarcity's effect on referrals). Future studies should attempt to shed more light on how different types of nudges may interact in different parts of the conversion funnel and different contexts. Analyzing interaction effects between Fleischmann et al. (2014)'s nudges from different root categories

of cognitive biases, based on the psychological process through which they affect decision making, at different stages of the conversion funnel would be a great starting point.

The first two studies contribute towards IS research on digital business models and digital nudges by expanding extant research on acquisitions in respect to how nudges may be leveraged to drive better acquisition outcomes through enhancing consumer referrals. Furthermore, we contribute directly to IS research on ewom and interactive marketing research by expanding our understanding of the antecedents of consumer referrals (King et al. 2014). Lastly, by illuminating the psychological processes underlying the nudges' effects and revealing different interactions dependent on these, we contribute to IS research on cognitive biases as well as more general psychology research related to human decision-making.

The third study focused on advancing our understanding of how digital nudges may contribute to better customer conversion outcomes. The study takes place in the context of freemium business models which have become fairly popular in light of success stories such as Spotify. We found that free trial order nudges, which build on the effects of loss aversion, may be leveraged to enhance customer conversions, whereas they are more effective when the value discrepancy between the free and premium version is low. Hence, this study also demonstrates that the effectiveness of nudges may be greatly influenced by other external factors which moderate the psychological process through which a nudge influences consumer decision making. Future research should focus on explicating such moderators and develop a structured framework for analyzing these according to the part of the conversion funnel that is being optimized. This study contributes towards IS research on digital nudges and digital business models by expanding our understanding of how digital nudges may be used to enhance customer conversions. It further contributes to research on digital nudges more broadly by expanding the definition of nudges beyond the manipulation of user-interface design elements to encompass the design of user experience journeys within the digital context (e.g., start with free vs. start with premium version). Future studies on digital nudges should therefore also consider the differential design of user experience journeys, a part of design research that is increasingly focusing on the digital context (e.g., Cyr 2014; Lemon and Verhoef 2016), along with user interface elements when investigating how nudges may influence consumer decisions in digital choice environments. Lastly, this study also contributes towards research on free trials in the context of information-related experience goods (e.g., Shapiro and Varian 1998a) by examining the differential effects of different free trial strategies.

From a more abstract perspective, this thesis expands our understanding of digital nudges and how these may be used to enhance acquisition and conversion outcomes within the conversion funnel of digital business models, thus allowing to better capture the value that is being created through new products and services. Our studies also provide compelling empirical evidence to back up our theoretical contributions.

6.2 Practical Contributions

Beyond the theoretical contributions of this thesis, there are also a number of practical implications and recommendations which firms operating in digital business should consider. Our findings give guidance on how to capture more of the value that is being created through novel products and services. We provide recommendations on the design of an improved conversion funnel through the employment of digital nudges, specifically for enhancing aqusition and customer conversion outcomes. In terms of acquisitions, the results of the first and second study revealed how digital nudges may be used to improve referrals, a critical mechanism for acquiring new users in a day and age where message credibility is critical. The results suggest that digital nudges need to be used to manipulate the referral drivers which are most critical for user decision making within the context of the product or service that is being offered. For example, while scarcity and social proof are very effective in situations where building social currency is a strong motive for consumers to make referrals, nudges such as personalization may be a better choice when manipulating drivers that are linked to longterm relationships between the marketer and customer is more important. Furthermore, the strength of a nudge itself is an important factor that needs to be considered. Our first study suggested that scarcity for example needs to meet an upper threshold to become effective. In terms of customer conversions, our findings suggest that digital nudges may be used to manipulate drivers which are critical to consumer conversion decisions. However, aside from considering which decision drivers need to be influenced, we urge firms to also carefully employ digital nudges based on the business model they operate in and the goals they are trying to accomplish at any given point in time. The findings of our third study lead us to recommend that in the context of freemium business models, for example, firms which employ financially viable low free-premium value discrepancy strategies should employ a Premiumfirst strategy because it allows them to benefit from free advertising effects without sacrificing conversion rates. In contrast, when high value discrepancy is employed due to economic or other reasons, firms should rather revert to the more traditional Freefirst strategy as placing every user in a time-limited premium trial from the very start equates to a large upfront investment that may never be recouped.

Overall, our results from the third study demonstrated the potential of employing the differential designs of user experience journeys (e.g., free trial order nudges) as digital nudges. Thus firms need to consider this as a valid alternative to changing user-interface design elements. Lastly, digital nudges need to be carefully employed and combined with each other, not only in terms of understanding the underlying drivers of consumer decision making they intend to affect, but also in regards to the different psychological paths through which nudges operate and thus may interact with each other. For example, our first and second study demonstrate that while social proof and scarcity nudges work well together, the effects of personalization are completely undermined when combined with scarcity. Thus, understanding these nuances and combining these digital nudges appropriately is key to enhancing the conversion funnel efficiency of digital business models.

In conclusion, this thesis contributes towards our understanding of how digital nudges may enhance the conversion funnel of digital business models. While the various drivers of consumer decision making in every part of the funnel and across different contexts are critical, understanding the psychological processes through which nudges affect human decision making as well as the overall business goals a firm is trying to drive are equally important. Only with an integrated perspective of these components can one truly capture more value by enhancing the conversion funnel. We hope that our research provides impetus for further analysis on the subject.

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