Three Essays on Analyzing and Managing Online Consumer Behavior

Inaugural-Dissertation
zur Erlangung des Doktorgrades
des Fachbereichs Wirtschaftswissenschaften
an der Wirtschaftswissenschaftlichen Fakultät
der Universität Passau

vorgelegt von

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Dissertation an der
Wirtschaftswissenschaftlichen Fakultät
der Universität Passau

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Datum der Disputation:	20. November 2014

Summary

Over the last two decades, the Internet has fundamentally changed the ways firms and consumers interact. The ongoing evolution of the Internet-enabled market environment entails new challenges for marketing research and practice, including the emergence of innovative business models, a proliferation of marketing channels, and an unknown wealth of data. This dissertation addresses these issues in three individual essays.

Study 1 focuses on business models offering services for free, which have become increasingly prevalent in the online sector. Offering services for free raises new questions for service providers as well as marketing researchers: How do customers of free e-services contribute value without paying? What are the nature and dynamics of nonmonetary value contributions by nonpaying customers? Based on a literature review and depth interviews with senior executives of free e-service providers, Study 1 presents a comprehensive overview of nonmonetary value contributions in the free e-service sector, including not only word of mouth, co-production, and network effects but also attention and data as two new dimensions, which have been disregarded in marketing research. By putting their findings in the context of existing literature on customer value and customer engagement, the authors do not only shed light on the complex processes of value creation in the emerging e-service industry but also advance marketing and service research in general.

Studies 2 and 3 investigate the analysis of online multichannel consumer behavior in times of big data. Firms can choose from a plethora of channels to reach consumers on the Internet, such that consumers often use a number of different channels along the customer journey. While the unprecedented availability of individual-level data enables new insights into multichannel consumer behavior, it also makes high demands on the efficiency and scalability of research approaches.

Study 2 addresses the challenge of attributing credit to different channels along the customer journey. Because advertisers often do not know to what degree each channel actually contributes to their marketing success, this attribution challenge is of great managerial interest, yet academic approaches to it have not found wide application in practice. To increase practical acceptance, Study 2 introduces a graph-based framework to analyze multichannel online customer path data as first- and higher-order Markov walks. According to a comprehensive set of criteria for attribution models, embracing both scientific rigor and practical applicability, four model variations are evaluated on four, large, real-world data sets from different industries. Results indicate substantial differences to existing heuristics such as “last click wins” and demonstrate that insights into channel effectiveness cannot be generalized from single data sets. The proposed framework offers support to practitioners by facilitating objective budget allocation and improving team decisions and allows for future applications such as real-time bidding.

Study 3 investigates how channel usage along the customer journey facilitates inferences on underlying purchase decision processes. To handle increasing complexity and sparse data in online multichannel environments, the author presents a new categorization of online channels and tests the approach on two large clickstream data sets using a proportional hazard model with time-varying covariates. By categorizing channels along the dimensions of contact origin and branded versus generic usage, Study 3 finds meaningful interaction effects between contacts across channel types, corresponding to the theory of choice sets. Including interactions based on the proposed categorization significantly improves model fit and outperforms alternative specifications. The results will help retailers gain a better understanding of customers’ decision-making progress in an online multichannel environment and help them develop individualized targeting approaches for real-time bidding.

Using a variety of methods including qualitative interviews, Markov graphs, and survival models, this dissertation does not only advance knowledge on analyzing and managing online consumer behavior but also adds new perspectives to marketing and service research in general.

Acknowledgments

This project would not have been possible without the support of many. First and foremost, I want to express my deepest gratitude to my advisor Jan Schumann for his continuous support, encouragement, and inspiration. I count myself incredibly lucky to have you as a mentor. Many thanks also go to my second advisor Florian von Wangenheim for his invaluable guidance and for immediately welcoming me into the DTM "family."

Without my colleagues in Munich and Passau this dissertation would not be the same—and writing it would have been much less fun. Thank you so much to all of you! Armin März deserves a special mention for being a great partner in crime and roommate from day one. I would also like to thank my other co-authors Ingo Becker, Werner Kunz, and Sebastian Klapdor, as well as my cooperation partners at intelliAd, Feld M, and ValueClick. It was a pleasure to work with you.

I gratefully acknowledge the institutional support I have received during my dissertation. My study was conducted in the context of the project "Fre(E)S: Produktivität kostenfreier E-Services" (FKZ: 01FL10038), which was funded by the German Federal Ministry of Education and Research (BMBF) and supported by the German Aerospace Center (DLR). A big thank you also goes to Passau University for providing me with the means to finish this dissertation and to Technische Universität München, the University of Massachusetts Boston, and the Cambridge Public Library for giving me shelter. Special thanks to Werner Kunz for inviting me to Boston and being a great mentor during my time in the US and beyond!

I sincerely thank my friends and family for pushing me to take on this challenge and keeping my spirit up along the way. Finally, thank you, Sebastian, for accompanying me on this journey—and for all the rest.

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AIC	Akaike Information Criterion
AUC	Area under ROC Curve
BIC	Bayesian Information Criterion
CCLV	Connected Customer Lifetime Value
CEB	Customer Engagement Behavior
CEV	Customer Engagement Value
CIC	Customer-Initiated Channel
CICBranded	Branded Customer-Initiated Channel
CICGeneric	Generic Customer-Initiated Channel
CLV	Customer Lifetime Value
CRV	Customer Referral Value
eWOM	Electronic Word of Mouth
FIC	Firm-Initiated Channel
GDP	Gross Domestic Product
GPS	Global Positioning System
HMM	Hidden Markov Model
NMCVC	Nonmonetary Customer Value Contribution
OLS	Ordinary Least Squares
RFID	Radio Frequency Identification
ROC	Receiver Operating Characteristic
SDL	Service-Dominant Logic
SE	Standard Error
SEA	Search Engine Advertising
SEO	Search Engine Optimization
Std. Dev.	Standard Deviation
SVAR	Structural Vector Autoregression

TV	Television
UGC	User-Generated Content
URL	Uniform Resource Locator
WOM	Word of Mouth

> The pervasiveness of the Internet, and its increasing and widespread influence as an information source, marketplace, and setting for social contact, have sparked growing interest in studying what people do online and how their behavior can be predicted and influenced.
>
> (Bucklin & Sismeiro, 2009, p. 35)

1 Introduction

1.1 The Digital Economy: Impact and Challenges

Over the last two decades, the Internet has fundamentally changed the ways firms and consumers interact (Hennig-Thurau et al., 2010). Both the number of Internet users as well as daily usage are continuously growing: In 2013, 54.2 million people in Germany, corresponding to 77.2% of the German population, used the Internet at least occasionally, spending on average 169 minutes per day online (van Eimeren & Frees, 2013). By 2016, nearly half of the world's population are expected to be online (Boston Consulting Group, 2012). As a consequence, e-businesses have become an integral part of the global economy: Worldwide, more than one billion consumers have made at least one digital purchase in 2013 (eMarketer, 2013b), bringing the global B2C e-commerce market to a size of $1.25 trillion (eMarketer, 2014). Overall, the Internet economy represented 4.1% of GDP in the G20 countries in 2012—with increasing tendency (Boston Consulting Group, 2012).

The ongoing evolution of the Internet-enabled market environment has had a major impact on contemporary marketing research and practice. New opportunities and challenges emerging in the digital economy are shaping the marketing research agenda (Varadarajan & Yadav, 2009). In particular, prior research has identified three prominent challenges (Leeflang, Verhoef, Dahlström, & Freundt, 2014), which we will delineate in the following subsections: the development of new business models, a proliferation of touchpoints and channels, and an increasing prevalence of data.

1.1.1 New Business Models

New digital businesses are currently sprouting in a "Cambrian explosion," which is reshaping entire industries (Siegele, 2014). Providing services via electronic networks has not only become a new business paradigm (Rust & Kannan, 2003), but the "network economy" (Shapiro & Varian, 1998) has also fostered the emergence of novel, innovative business models. Even the term business model itself has largely been coined in the digital economy, as there was very little academic research on this topic before 1995 (Coombes & Nicholson, 2013; Ehret, Kashyap, & Wirtz, 2013; Osterwalder, Pigneur, & Tucci, 2005). Although research interest in business models has grown substantially over the last 20 years, scholars do not agree on the definition of the concept (Coombes & Nicholson, 2013; Zott, Amit, & Massa, 2011). As value creation and value capture seem central to a number of studies (Coombes & Nicholson, 2013; Zott et al., 2011),[1] we define a business model as "the rationale of how an organisation creates, delivers, and captures value" (Osterwalder & Pigneur, 2010, p. 14).

New opportunities of connecting customers online have fostered the development of digital platform business models (Bakos & Katsamakas, 2008; Brousseau & Penard, 2007; Sriram et al., 2014). Platforms act as intermediaries in two-sided or multisided markets (Eisenmann, Parker, & van Alstyne, 2006, 2011; Rochet & Tirole, 2003, 2006), enabling interactions between distinct customer populations. Examples include marketplaces connecting buyers and sellers, such as eBay, or content platforms linking producers and consumers of digital media, such as iTunes or Netflix (Bakos & Katsamakas, 2008). Multisided markets are not limited to the online world—consider for example the credit card or the newspaper industry—but have become much more prevalent in the digital economy (Eisenmann et al., 2006).

To capture value in multisided markets, platform providers need to negotiate a number of challenges. First, because of increasing returns to scale and network effects, multisided markets are prone to winner-take-all dynamics (Eisenmann et al., 2006; Noe & Parker, 2005). Second, even if they successfully address the winner-take-all challenge, intermediaries risk being enveloped by adjacent providers (Eisenmann et al., 2006, 2011). Finally, serving multiple customer groups raises

[1] See for example Chesbrough (2007), Johnson, Christensen, and Kagermann (2008), and Teece (2010).

pricing issues because platform providers have to choose a price for each customer group, one of which is often subsidized (Eisenmann et al., 2006). In the extreme case, one customer group receives services for free, leading to a complete separation of usage and payment. Facilitated by low to minimal marginal costs, such business models offering services for free are spreading rapidly in the online sector (Anderson, 2009; Bryce, Dyer, & Hatch, 2011; Casadesus-Masanell & Zhu, 2013). To monetize their services in a sustainable way, providers of free e-services need to understand the value of their nonpaying customers—to their own firm and to paying third parties. Marketing research thus needs to go beyond the consumer–firm dyad and to consider more complex multiparty interactions in a system environment (Yadav & Pavlou, 2014).

1.1.2 Proliferation of Channels

The practice of multichannel marketing has grown significantly over the last years (Neslin & Shankar, 2009). Though selling through multiple channels is not a new phenomenon, the emergence of integrated multichannel retailing was largely driven by the ascent of the Internet (Zhang et al., 2010). Prior research has shown that multichannel customers buy more and are more valuable than average single channel customers (Ansari, Mela, & Neslin, 2008; Kumar & Venkatesan, 2005; Neslin et al., 2006). Yet, the evaluation of and resource allocation between channels in a multichannel environment is nontrivial, especially given synergies and cross-channel effects (Neslin et al., 2006). For instance, research shoppers gather information in one channel but make the final purchase in another channel (Verhoef, Neslin, & Vroomen, 2007).

Besides employing multiple delivery channels, firms can also choose from a plethora of marketing vehicles to reach consumers. Online marketing channels include—among others—display, paid search, mobile, and social media advertising (Raman, Mantrala, Sridhar, & Tang, 2012). Compared to traditional marketing channels, such as television (TV), print, and radio, online marketing channels offer a higher degree of interactivity, such that consumers can show a direct behavioral response by clicking on advertisements (Chatterjee, Hoffman, & Novak, 2003). In addition, digital consumers have ample opportunity “to talk back and talk to each other’’ (Deighton & Kornfeld, 2009, p. 4), for example by reading and writing online reviews (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Today, such “social earned” channels, which are often not under the control of the firm, complement the range of paid and owned marketing channels (Stephen & Galak, 2012, p. 624).

The proliferation of digital marketing channels entails a number of challenges for marketing managers. Consumers may be exposed to advertisements through various channels along their "customer journey" (Lee, 2010),[2] yet marketing managers lack transparency about the degree to which each channel or campaign contributes to their companies' success. In practice, the challenge of awarding credit to different channels is often addressed by simple heuristics, such as "last click wins," such that the value gets attributed solely to the marketing channel that directly preceded the conversion, and any prior customer interactions are disregarded (Econsultancy, 2012a). Despite its practical relevance, marketing attribution only recently has become a focus for marketing researchers (Abhishek, Fader, & Hosanagar, 2012; Berman, 2013; Haan, Wiesel, & Pauwels, 2013; Kireyev, Pauwels, & Gupta, 2013; Li & Kannan, 2014; Xu, Duan, & Whinston, 2014). However, to the best of our knowledge, sophisticated attribution approaches have not found wide application in practice.

Given the increasing number of possible online touchpoints, Yadav and Pavlou (2014) identify a need to (re)investigate the structure of consumers' purchase decision processes. Although purchase decision processes and consideration set formation have long been discussed in the marketing literature (Hauser & Wernerfelt, 1990; Howard & Sheth, 1969; Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991), the ability to track online marketing exposures over multiple channels provides new opportunities for analyzing the "path to purchase" (Xu et al., 2014). Using data on multichannel behavior to investigate underlying purchase decision processes requires new approaches to categorize marketing channels though, which often evolve more rapidly than corresponding research efforts (Yadav & Pavlou, 2014). So far, the digital world has in parts developed faster than the tools needed to measure it (Bughin, Shenkan, & Singer, 2008) and marketing research does not fully capture the increasing richness and complexity of firms' online marketing activities (Yadav & Pavlou, 2014).

1.1.3 Big Data

The increasing complexity of the marketing environment is accompanied by an unprecedented wealth of data to observe and measure consumer behavior. The Internet allows for fast, easy, and unobtrusive collection of detailed information on

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[2] An online customer's journey includes all contacts of an individual customer with a brand over all online channels preceding a potential purchase decision.

individual activities (Bucklin & Sismeiro, 2009), on a level of a granularity that was unheard-of in the offline world (Bijmolt et al., 2010). Every day, consumers leave a massive trail of data:

> Data are created and stored when we visit a Web site, when we buy, when we are exposed to an ad, when we click, when we message. More data are created when we simply move about town, or when we play games. Even little family businesses with the odd, occasional Web visitor can generate megabytes of the stuff each month. And social networks? My how people talk. And upload pictures. And post, chat, comment, like, link and review. Hundreds of different behaviors being captured by dozens of different types of sites and apps on four or five different types of devices. All day, every day. (Hofacker, 2012, pp. 1–2)

This abundance of data provides new opportunities and challenges for marketing managers. As discussed above, online data offer new ways to investigate well-known phenomena such as the modeling of decision making processes and stages (Bucklin & Sismeiro, 2009). They also provide new opportunities for personalization (Bucklin & Sismeiro, 2009) and enable firms to target customers individually (Varadarajan & Yadav, 2009). Prior research has shown that customized e-mail communication based on clickstream data increases the number of click-throughs to the website (Ansari & Mela, 2003) and that targeted advertising leads to higher profits (Iyer, Soberman, & Villas-Boas, 2005). Personalized recommendation systems can also reduce consumers' information overload (Adomavicius & Tuzhilin, 2005; Xiao & Benbasat, 2007) and have a positive impact on sales (Pathak, Garfinkel, Gopal, Venkatesan, & Yin, 2010). Overall, marketing analytics based on market and customer data can help firms to sustainably increase their performance, especially in highly competitive industries (Germann, Lilien, & Rangaswamy, 2013).

"Big data" are defined by their volume, velocity, and variety, thereby challenging existing approaches for data management and analysis (Chen, Chiang, & Storey, 2012; Laney, 2001; McAfee & Brynjolfsson, 2012). The sheer volume of data has evoked imaginative metaphors: "Exploding volumes of data" (Germann et al., 2013, p. 114) lead to a "data deluge" (Economist, 2010), such that companies are "drowning in data" (Hofacker, 2012, p. 1). Consumers conduct 32 billion searches on Google every month and compose 50 million tweets per day (Leeflang et al., 2014). The speed of data creation and analytics is another critical issue, especially for applications in (near) real-time. Efficient applications are especially important in the mobile sector where data are time- and location sensitive (Luo, Andrews, Fang, & Phang, 2014; Shankar, Venkatesh, Hofacker, & Naik, 2010). In online ad exchanges, advertisers can bid on advertising slots for specific users in real time, requiring decisions in milliseconds (Muthukrishnan, 2009). In combination, volume and velocity create a need for new analytic approaches, as traditional methods are often not applicable because of computational resource constraints (Bijmolt et al., 2010). The variety of data on online consumer behavior, which are often unstructured, also requires innovative techniques, such as social network analytics or text-mining (Chen et al., 2012; Malthouse, Haenlein, Skiera, Wege, & Zhang, 2013). For example, Ludwig et al. (2013) analyze the semantic content and style properties of unstructured customer reviews in order to examine the influence of electronic word of mouth (eWOM) on the conversion rates of online retail sites. In addition to handling the volume, velocity, and variety of data, marketers need to be aware of privacy concerns (Goldfarb & Tucker, 2012; Malhotra, Kim, & Agarwal, 2004; Schumann, Wangenheim, & Gröne, 2014). Consumers become increasingly privacy-protective (Goldfarb & Tucker, 2012), such that marketing managers need to weigh privacy concerns and data richness (Malthouse et al., 2013).

Academic marketing researchers often “struggle to balance the needs of in-depth understanding, causal explanation, and predictive accuracy” related to big data (Dholakia & Dholakia, 2013, p. 26). Day (2011) laments a widening capabilities gap with regards to data, which is confirmed by a recent survey among marketing managers (Leeflang et al., 2014). Marketing research thus needs to develop new methods to analyze online data—and to convince practitioners without in-depth statistical knowledge of actually using them (Lilien, 2011). In consequence, the Marketing Science Institute (2014) has declared “developing marketing analytics for a data-rich environment” a tier one priority for marketing researchers.

1.2 Research Scope

This dissertation addresses three major challenges emerging in the Internet-enabled market environment, which we have outlined above, in three independent studies. In the following subsections, we provide a brief overview of these studies and present our research scope.

1.2.1 Study 1: There Is No Such Thing as a Free Lunch: Nonmonetary Customer Value Contributions in Free E-Services

The evolution of innovative business models in the digital economy raises new questions for academia and practice. In Study 1, we specifically focus on business models offering services for free, which have become increasingly prevalent in the online sector (Anderson, 2009; Bryce et al., 2011; Brynjolfsson & Oh, 2012; Casadesus-Masanell & Zhu, 2013). While free offers have long been in use as marketing incentives or bundled with other products or services outside the digital economy (Bawa & Shoemaker, 2004; Kamins, Folkes, & Fedorikhin, 2009), marketing research has only recently begun to address cases in which offering a service for free to at least a segment of the customer base is part of the main business model (Gupta & Mela, 2008; Halbheer, Stahl, Koenigsberg, & Lehmann, 2014; Papies, Eggers, & Wlömert, 2011; Pauwels & Weiss, 2008).

Even though researchers have long recognized that direct revenues are not the only relevant source of customer value (Danaher, Rust, Easton, & Sullivan, 1996; Rust, Zahorik, & Keiningham, 1995; Zeithaml, 2000), there is scant research on nonmonetary customer value contributions by free e-service customers who do not pay anything at all. Study 1 addresses this gap by examining the following research questions:

1) How do customers of free e-services contribute value without paying?
2) What are the nature and dynamics of nonmonetary value contributions by nonpaying customers in free e-services?

1.2.2 Study 2: Mapping the Customer Journey: A Graph-Based Framework for Online Attribution Modeling

Monetizing attention by means of advertising is one of the most important revenue models for free e-service providers: customers “pay” with attention and e-service providers act as “attention brokers” (U.S. Patent No. 5794210, 1998). In an online multichannel environment, both e-service providers relying on advertising as a revenue model and online marketers using advertising to promote their products and services need to develop a better understanding of advertising effectiveness. To efficiently allocate budgets, marketing executives call for new metrics to evaluate the contribution of each (online) marketing channel (Econsultancy, 2012a; Ramsey, 2009). Solving this attribution challenge should also result in fairer remuneration for advertising-financed e-service providers (Jordan, Mahdian, Vassilvitskii, & Vee, 2011).

Modern tracking solutions that allow advertisers to record individual-level customer journeys across all online marketing channels enable new ways of addressing the attribution problem (Bucklin & Sismeiro, 2009). Nevertheless, the majority of advertisers rely on simple heuristics, such as “last click wins,” attributing the value solely to the marketing channel that directly precedes a conversion (Econsultancy, 2012a). Despite its high managerial relevance, attribution has only recently sparked the interest of marketing researchers (Abhishek et al., 2012; Berman, 2013; Haan et al., 2013; Kireyev et al., 2013; Li & Kannan, 2014; Xu et al., 2014). However, these academic approaches have not found wide application in practice—potentially because analytical rigor is a necessary but not a sufficient condition for gaining acceptance in the managerial world (Wübben & Wangenheim, 2008). To reach managerial acceptance, an attribution framework also needs to fulfill more practice-oriented criteria, especially considering the volume and complexity of individual-level customer journey data. Study 2 therefore takes a practice-oriented approach to address the attribution problem by investigating the following research questions:

3) What are relevant criteria for an attribution framework to embrace both scientific rigor and practical applicability?
4) Which framework can be applied to ascertain the correct value contribution of each online marketing channel?

1.2.3 Study 3: Analyzing Multichannel Online Customer Journeys for an Online Retailer: A Categorization Approach

With a focus on analyzing multichannel online customer journeys, Study 3 is again located at the interface between multichannel marketing and big data. Despite an ever-evolving spectrum of online marketing channels (Evans, 2009)—on average, European marketers report using seven channels in parallel (Teradata Corporation, 2013)—academic research on online marketing in a multichannel environment is only beginning to gain momentum. Until recently, online marketing research primarily investigated the effectiveness of single channels such as display and search in isolation. Most existing studies on multichannel online marketing also focus on the interplay of selected channels, especially display and search (Abhishek et al., 2012; Kireyev et al., 2013; Lewis & Nguyen, 2014; Nottorf, 2014; Papadimitriou, Krishnamurthy, Lewis, Reiley, & Garcia-Molina, 2011; Xu et al., 2014). Outside of few recent exceptions (Anderl, Becker, Wangenheim, & Schumann, 2014; Klapdor, 2013; Li & Kannan, 2014), mainly in the context of attribution, there is scant research covering the full spectrum of online channels available to online retailers.

Tracking multichannel customer journeys on an individual level across all online marketing channels may allow inferences on underlying purchase decision processes, thus answering a call to reinvestigate consumer decision-making in an online context (Yadav & Pavlou, 2014). However, at the same time, the growing number of online marketing channels used in parallel increases the complexity of individual-level analyses, as data points become sparse with rising dimensionality. This so-called “curse of dimensionality” (Bellman, 1961) creates a need for new approaches to reduce complexity. Study 3 hence investigates the following research questions:

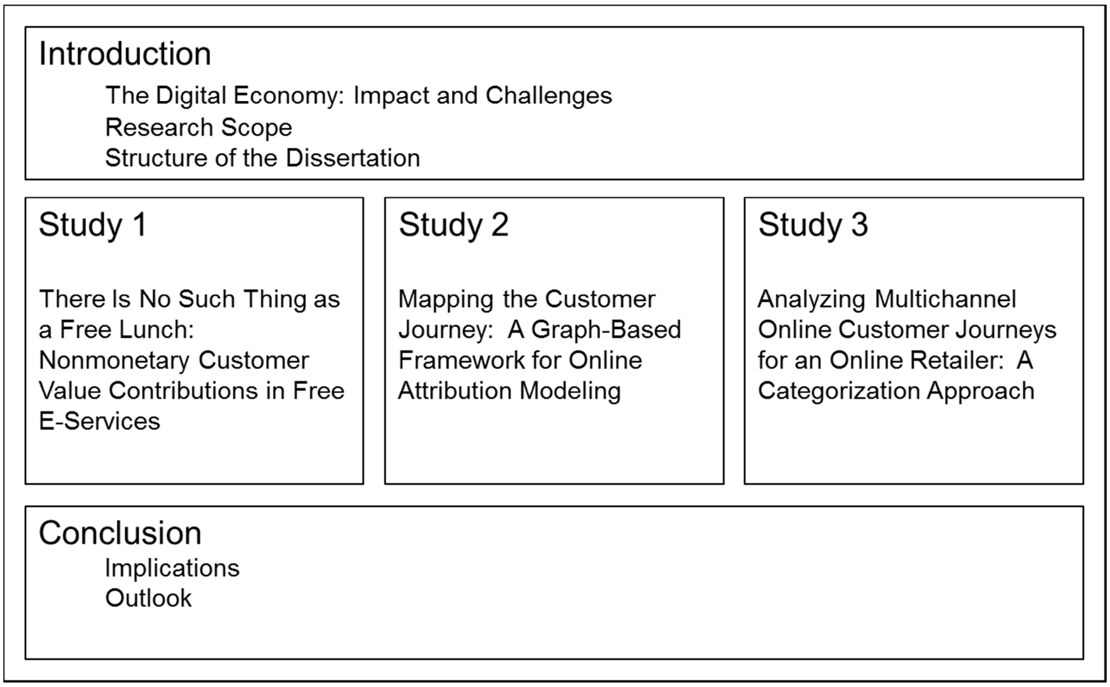
5) Does channel usage along the customer journey facilitate inferences on underlying purchase decision processes?
6) How can online marketing channels be categorized to investigate the interplay between channels along the customer journey?

1.3 Structure of the Dissertation

This dissertation proceeds as follows: After giving an overview of the digital economy and the challenges it provides for marketing academia and practice and discussing our research scope, we continue with Study 1 on nonmonetary customer value contributions in free e-services. We present this study in Chapter 2. Chapter 3 comprises Study 2 on online attribution modeling. Next, we present Study 3, which investigates the categorization of online marketing channels in order to draw inferences on underlying purchase decision processes, in Chapter 4. In Chapter 5, we end with a summary of implications and an outlook on future research. Figure 1 outlines the overall structure of this dissertation.

Figure 1

Structure of the Dissertation



2 There Is No Such Thing as a Free Lunch: Nonmonetary Customer Value Contributions in Free E-Services

Eva Anderl, Armin März, Jan H. Schumann

Offering services for free, which is becoming a prevalent business model online, raises new questions for service providers as well as marketing researchers: How do customers of free e-services contribute value without paying? What are the nature and dynamics of nonmonetary value contributions by nonpaying customers? Based on a literature review and depth interviews with senior executives of free e-service providers, the authors present a comprehensive overview of nonmonetary value contributions in the free e-service sector, including not only word of mouth, co-production, and network effects but also attention and data as two new dimensions, which have been disregarded in marketing research. By putting their findings in the context of existing literature on customer value and customer engagement, the authors do not only shed light on the complex processes of value creation in the emerging e-service industry but also advance marketing and service research in general.

2.1 Introduction

Business models offering services for free have become increasingly prevalent—especially in the online sector (Anderson, 2009; Bryce et al., 2011; Casadesus-Masanell & Zhu, 2013). Consumers can choose from a multitude of free e-services, ranging from online search and communication to entertainment and social networking without paying for their usage. Largely driven by the growth of free e-services, where offering services at a price of zero is facilitated by low to minimal marginal costs, the overall market size of this “freeconomy” was estimated at $260–$300 billion in 2009 (Anderson, 2009). Major investments, such as Facebook’s recent acquisitions of WhatsApp for approximately $19 billion and Instagram for $1 billion, indicate that the market for nonpaying users is not only lucrative but also highly competitive (Gelles & Goel, 2014). Even as free e-service business models spread rapidly though, academic research on how customers of these services contribute value without paying remains surprisingly scarce.

Despite ample research on free products and services as marketing incentives (Bawa & Shoemaker, 2004), trial versions (Jiang & Sarkar, 2009), or in bundles with other products or services (Kamins et al., 2009), researchers have only recently begun to address cases in which offering a service for free to at least a segment of the customer base is part of the main business model[3] and not just a marketing tool. Several studies investigate moving from free to fee (Pauwels & Weiss, 2008) and the willingness to pay for free content (Halbheer et al., 2014; Papies et al., 2011). Finally, the management literature has started to research competitive strategies when facing free or sponsor-based business models (Bryce et al., 2011; Casadesus-Masanell & Zhu, 2013).

However, there is scant research on nonmonetary customer value contributions (NMCVCs), i.e., resource contributions by customers that do not include a monetary transaction, in services that are completely free to the end customer. While researchers have long recognized that direct revenues are not the only relevant source of customer value[4] (Danaher et al., 1996; Rust et al., 1995; Zeithaml, 2000), this study focuses on customers who contribute in a number of ways but do not generate any direct revenues. For a provider of free e-services, the main NMCVCs that have been discussed to date—word of mouth (WOM), co-production, and network effects—seem to play an important role, yet they do not cover a customer's full value contribution and the resulting opportunities for monetization, that is the generation of monetary revenues. Many free e-service providers rely on monetizing attention in form of advertising and the use of personal data, so it is surprising that these aspects have not been discussed in the academic literature. Besides, it is unclear whether and how the nature and dynamics of previously discussed NMCVCs change in a free e-service context.

To fill this gap, we conducted an interview study with 23 senior executives of free e-service providers. We identify important dimensions and roles of NMCVCs in the free e-service sector and discuss our results in the context of existing research on customer value and customer engagement. The contribution of our research is at least fivefold: First, we conceptualize attention and data as two new dimensions of

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[3] We understand a business model as the "rationale of how an organisation creates, delivers, and captures value" (Osterwalder & Pigneur, 2010, p. 14).

[4] Throughout this paper, we use the term "customer value" to cover the value of a customer to the firm and do not cover alternative usages that take a customer perspective (e.g. Payne, Storbacka, & Frow, 2008).

NMCVCs that are core constituents of many free e-service business models. Even though both dimensions extend beyond the free e-service domain, they have so far been disregarded in research on customer value. Second, we contribute to customer engagement literature (Brodie, Hollebeek, Juric, & Ilic, 2011; Jaakkola & Alexander, 2014; Kumar, Aksoy et al., 2010; van Doorn et al., 2010) by exploring the definitional boundaries of customer engagement behaviors (CEBs). Both attention and data seem to be of a semi-motivational nature, such that they only partly comply with the existing definition of CEBs as voluntary behaviors resulting from motivational drivers. The fact that a clear distinction between motivational and nonmotivational behaviors is not possible for attention and data limits the discriminatory power of the existing CEB definitions and thus provides opportunities for future research and theory refinement. Third, we contribute to research on the emerging free e-service sector by elaborating the nature and dynamics of NMCVCs in free e-services. We confirm WOM, co-production, and network effects as important NMCVCs for e-service providers and identify attention and data as additional dimensions, thereby providing a comprehensive overview of NMCVCs in the free e-service industry. In addition, we extend existing knowledge on co-production and network effects by identifying three subtypes of co-production that are of special importance in free e-services and distinguish three generic drivers for network effects. Fourth, we contribute to research on value co-creation in networked environments in service-dominant logic (SDL; Lusch & Vargo, 2006; Vargo & Lusch, 2008). Because free e-services seem to undermine the generalizability of selected SDL foundational premises, Kuppelwieser, Simpson, and Chiummo (2013, p. 319) call for a reexamination of SDL in the context of free e-services. By providing an exhaustive analysis of value creation in the free e-service industry, our research constitutes an important step for a deeper discussion of SDL in this unique setting. Fifth, our conceptualization of NMCVCs in free e-services can help change managerial perceptions. Understanding nonmonetary value contributions is an essential first step for e-service providers to establish and manage customer relationships with their nonpaying customer base. Before we focus on the free e-service industry, we begin with an overview of the existing literature on NMCVCs to put our findings into context.

2.2 Literature Review: NMCVCs

Since the first appeals to include WOM and other social effects when determining customer value (Danaher et al., 1996; Rust et al., 1995; Zeithaml, 2000), a proliferation of studies have discussed NMCVCs. While most approaches for calculating customer lifetime value (CLV), which is one of the most widely used and accepted measures of customer value (Gupta et al., 2006; Jain & Singh, 2002), focus on transaction behavior and direct revenues from customers (Gupta et al. 2006; Venkatesan and Kumar 2004), several researchers have proposed to extend the definition of CLV to cover selected NMCVCs. Examples include cost savings for customer acquisition (Lee, Lee, & Feick, 2006) or an advertising ripple effect (Hogan, Lemon, & Libai, 2004). Recently, selected NMCVCs have gained increased attention in customer engagement literature (Brodie et al., 2011; Jaakkola & Alexander, 2014; Kumar, Aksoy et al., 2010; van Doorn et al., 2010): Kumar, Aksoy et al. (2010) introduce customer engagement value (CEV) as a broader concept that includes CLV as well as value through other CEBs, namely customer referral value, customer influencer value, and customer knowledge value. Other researchers explicitly limit CEV to voluntary resource contributions that go beyond purchase transactions (Jaakkola & Alexander, 2014; van Doorn et al., 2010).

In Table 1, we provide an overview of the existing literature on NMCVCs in chronological order, including the dimensions in focus, the research approach, the industry context, and key findings. Because some NMCVC dimensions have been subject to extensive research, we only added studies that explicitly examine the value of NMCVCs. The main NMCVC dimensions that have been discussed in prior research are WOM, co-production, and network effects. As the second column from the right in Table 1 shows, prior research mostly covers NMCVCs as complements to monetary revenues. Studies on NMCVCs in the free e-service sector are scant and predominantly focus on single NMCVC dimensions.

Table 1

Existing Literature on NMCVCs—Study 1

Study	Dimensions of NMCVC					Research approach	Free e-service context	Main findings on NMCVCs
	WOM	Co-production	Network effects	Attention	Data			
Rust et al. (1995)	X					Conceptual		Return on quality: customer satisfaction leads to positive WOM, attracting new customers and leading to increased revenues
Danaher et al. (1996)	X					Empirical		Indirect benefits of service quality: improved customer perceptions result in increased attraction of new customers
Zeithaml (2000)	X					Conceptual		Economic worth of customers as a question for further research: How can WOM communication from retained customers be quantified?
Domingos and Richardson (2001)			X			Empirical		Network value of a customer: expected profit from sales to other customers who are influenced to buy
Ryals (2002)	X	X				Conceptual		Benefits of long-term relationships: process efficiency (learning and innovation), new customer acquisition (referrals and referencability), relationship benefits
Helm (2003)	X					Conceptual		Calculating the monetary referral value of customers through positive WOM
Hogan, Lemon, and Libai (2003)	X					Empirical		Value of a lost customer: influence of social effects (WOM, imitation) on future customer acquisition
Stahl, Matzler, and Hinterhuber (2003)	X	X				Conceptual		CLV needs to take into account both monetary and nonmonetary aspects: networking potential (WOM) and learning potential
Hogan et al. (2004)	X					Empirical		WOM and advertising effectiveness: total CLV = conventional CLV + advertising ripple effect (value of customers acquired through positive WOM)
Algesheimer and Wangenheim (2006)			X			Conceptual		Network-based approach to customer equity management: including indirect effects into CE calculations
Lee et al. (2006)	X					Empirical		Incorporating WOM effects in estimating CLV: impact of WOM on CLV through cost savings for new customer acquisition
Kumar, Petersen, and Leone (2007)	X					Conceptual Empirical		Value of WOM: customer value = value from purchases (CLV) + referral value
Wangenheim and Bayón (2007)	X					Empirical		Chain from customer satisfaction through WOM referrals to customer acquisition

Study	Dimensions of NMCVC					Research approach	Free e-service context	Main findings on NMCVCs
	WOM	Co-production	Network effects	Attention	Data			
Cook (2008)		X				Conceptual	X	Overview of “user contributions”: taxonomy, advantages, outcomes, and motivational aspects
Gupta and Mela (2008)			X			Empirical	X	Value of nonpaying customers for an auction website taking into account direct and indirect network effects
Ryals (2008)	X	X				Conceptual Empirical		Determining the indirect value of a customer: including referrals and reference effects as well as learning and innovation
Villanueva, Yoo, and Hanssens (2008)	X					Empirical		Effect of WOM-based customer acquisition on customer equity growth
Trusov, Bucklin, and Pauwels (2009)	X					Empirical	X	Effect of WOM marketing on member growth at a social networking site
Hoyer, Chandy, Dorotic, Krafft, and Singh (2010)		X				Conceptual		Consumer co-creation in new product development: stimulators and impediments, impact of co-creation, and firm- and consumer-related outcomes
Jiang (2010)	X		X			Empirical	X	Free software offers as a promotional tool: due to WOM, free offers increase a firm's total profit
Kumar, Aksoy et al. (2010)	X	X				Conceptual		Conceptualizing CEV: CLV (= purchase behavior), customer referral value, customer influencer value, and customer knowledge value
Kumar, Petersen, and Leone (2010)	X					Conceptual Empirical		Driving profitability by encouraging customer referrals: new approach to compute customer referral value (CRV) and identification of behavioral drivers of CRV
Libai et al. (2010)	X					Conceptual		Customer-to-customer interactions: dimensions and business outcomes
Stephen and Toubia (2010)			X			Empirical	X	Economic value implications of a social network between sellers in an online social commerce marketplace
Trusov, Bodapati, and Bucklin (2010)			X			Empirical	X	Determining influential users that have significant effects on the activities of other users in online social networks
Tucker and Zhang (2010)			X			Empirical	X	Indirect network effects in two-sided networks: sellers prefer markets with many other sellers because they attract more buyers
van Doorn et al. (2010)	X	X				Conceptual		Theoretical foundations and research directions for CEBs
Iyengar, Bulte, and Valente (2011)	X		X			Empirical		Opinion leadership and social contagion in new product diffusion: contagion operating over network ties within online social networks

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

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

2.3 Methodology

To gain a better understanding of the dimensions and roles of NMCVCs in free e-services, we conducted an interview study with industry experts. Our qualitative sample consists of 23 senior executives of German free e-service providers with different business models and in different company stages. Following a grounded theory approach (Strauss & Corbin, 1990), we stopped our sampling procedure at the point of saturation. The total number of interviews we conducted is consistent with sample sizes recommended for exploratory research using in-depth interviews (Guest, Bunce, & Johnson, 2006; McCracken, 1998). We conducted interviews between January 2012 and February 2013, and they lasted between 40 and 75 minutes. Table 2 provides an overview of the interview participants.

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

Each interview was recorded and transcribed verbatim. Our analysis followed a grounded theory approach (Strauss & Corbin, 1990). Two researchers independently open-coded the transcripts to identify relevant concepts. After comparing and discussing the results and matching them with existing literature, we jointly developed a coding plan that included five major types of NMCVCs, subtypes for each NMCVC, outcomes, and managerial challenges. The final coding scheme consisted of 39 codes with 1996 quotations.

To ensure validity, we assessed intercoder reliability between the two judges for the final codings according to two measures. The proportional agreement of .86 is well above the recommended threshold of .8 (Neuendorf, 2002). The value of the Perreault and Leigh measure (Perreault & Leigh, 1989) is .92. This value exceeds both the .7 threshold recommended for exploratory research and the .9 cutoff point for advanced marketing research practice (Rust & Cooil, 1994). Therefore, we are confident that our results are valid and reliable. In the following section, we present the dimensions of NMCVCs in the free e-service sector, which we identified in our qualitative study, and put them in the context of the existing literature.

Table 2

List of Interview Participants—Study 1

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

2.4 NMCVCs in the Free E-Service Industry

2.4.1 WOM

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

Direct monetization of WOM by free e-service providers seems rare. A majority of respondents emphasized that the business value of WOM in free e-services lies in cost savings for customer acquisition: "We just spend a lot of money to generate traffic on our website, for search engine optimization, for search engine advertising, and for printed ads. When a user takes over this job, we immediately save money. And that's the value" (D82). While measuring WOM referrals on an individual level is relatively easy, influence is mainly seen as a "black box" (L121). Accordingly, managers of free e-services identify measurability as the most important managerial challenge related to WOM as an NMCVC. This finding is in line with prior research on CEB, where the value of intrinsically motivated influence by customers, conceptualized as customer influencer value, has not yet been analyzed in full detail (Kumar, Aksoy et al., 2010). New methods, such as linguistic analysis, are required to identify the value of unstructured eWOM and relate it to individual customers (Bijmolt et al., 2010; Malthouse et al., 2013).

2.4.2 Co-Production

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

Direct monetization of co-production by providers of free e-services is rare; although with exceptions: An online photo community is successfully experimenting with licensing customers' co-produced content for a commission fee (G132). Given the limited direct monetization, most respondents define the business value of co-production as cost savings for content production or support. Zhang et al. (2012) find that for a UGC platform, acquiring new content contributors has the largest cumulative financial value, followed by content consumer acquisition, contributor retention, and finally consumer retention.

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

2.4.3 Network Effects

Both *intramarket* and *cross-market network effects* play an important role in the free e-service domain. Intramarket network effects arise if the value of a service is an increasing function of the network’s size (Katz & Shapiro, 1985). Cross-market network effects occur in multisided markets when a firm offers different products or services in two or more markets and the value of one product or service depends on demand for the other (Chen & Xie, 2007). By linking paying and nonpaying customers, cross-market network effects often constitute the basis for monetizing free e-services. Although network externalities have been extensively covered in economics literature (see Stremersch, Tellis, Franses, & Binken, 2007), their inclusion in customer value or customer equity calculations is more recent. Gupta and Mela (2008) analyze the value of a nonpaying customer for an online auction platform, taking into account cross-market network effects among buyers, who do not pay anything to the platform, and sellers, who pay for brokerage services. Due to network effects, nonpaying customers can be valuable resources for a free e-service provider, “like metal in the automotive industry”: “This is comparable to the purchasing department of other companies. We pay for the acquisition and retention of nonpaying customers who we finally try to place in the job market" (E18).

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

Most of the managers we interviewed emphasized the value of the sheer number of nonpaying customers for attracting additional nonpaying as well as paying customers: "The mere fact of their existence and their existence in a significant number constitutes a value" (N104). This effect is enhanced in multisided markets, which are particularly prone to winner-take-all dynamics (Eisenmann et al., 2006): "If you are the dominant platform, you can just name your price. In fact, you could stop your marketing activities because sellers must use your platform anyway" (U53). In addition to quantity, we identify three qualitative drivers that determine a customer's contribution through network effects in free e-services. The network value of customers can be specified and amplified by (1) their *fit* with other customers, (2) their *reputation*, and (3) their degree of *interconnectedness* both within and outside the platform or community. These drivers work for both cross-market and intramarket effects but to varying extents. Fit and reputation of free customers ensure a compatible and attractive target group for third parties, such as advertisers or employers in a career network. The more detailed a free e-service provider can describe its target group, the more interesting the free customers become for paying third parties. Fit and interconnectedness are important drivers of intramarket effects for building or sustaining a homogeneous and interactive exchange (e.g., on social network sites or online browser games). Several managers reported that deviating user behavior by new customers of different culture or age groups confused and discouraged the existing customer base (C75, G124). While fit or assortativity and interconnectedness have been confirmed as drivers of network effects in specific contexts (Haenlein & Libai, 2013; Katona et al., 2011; Nitzan & Libai, 2011), these drivers seem to apply more broadly to most of the free e-services in our sample.

2.4.4 Attention

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

Attention is often the only customer value contribution that free e-services monetize more or less directly. Potentially the most widespread revenue model based on customer attention is advertising (Katona & Sarvary, 2008; Prasad, Mahajan, & Bronnenberg, 2003), which is a major revenue source for media and many free service providers (Anderson, 2009). Whereas advertising is paid mass-communication about a product or organization that can include both simple exposure and behavioral responses (Lamb, Hair, & McDaniel, 2009), successful brokerage always requires a behavioral response from the nonpaying customer. Brokers act as platforms to enable actual transactions between two parties and, as such, strongly rely on cross-market network effects. Free e-service examples include real-estate brokerage platforms, job markets, or other marketplaces.

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

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

Along with directly monetizing attention, many of the free e-service providers we interviewed take advantage of their customers’ attention to either upsell paid offerings or cross-sell additional services. In the freemium model, basic service is available to consumers for free, whereas premium services are only accessible for a fee (Oestreicher-Singer & Zalmanson, 2013; Vock et al., 2013). The free offer in freemium models is usually not limited in time and coexists simultaneously with chargeable premium versions (Teece, 2010), such that gaining the customers’ attention for upselling options is crucial for business success: “Attention helps us create new revenue streams” (A124). Cross-selling offerings in the free e-service domain often are again free—that is, there are no transaction fees between website operator and customer. For example, the manager of a comparison website for energy providers confirmed high cross-selling rates of customers who look for a new gas provider and later also change their energy supplier using the same service (T24).

2.4.5 Data

Most of our interview partners identify data as an important NMCVC in the free e-service domain: “The most important value contribution? In our case, that’s obviously data” (G88). Yet, to our knowledge, data have not previously been conceptualized as a customer value contribution in marketing and service literature—despite ongoing public discussions about big data, data security, and privacy. In addition to volunteered *profile data*, the e-service industry is able to gather a myriad of *behavioral data*, such as clicks and browsing patterns: “Data are extremely important for us to see how users move inside the platform. Which user uses which elements, posts activities, etc.?” (M34). There is a market value for certain types of customer data, especially address data, so that data can be translated into revenues via data intermediaries (Pancras & Sudhir, 2007). Prior research has shown how to use data to grow CLV by increasing marketing effectiveness and cross-selling through personalized recommendations (Bodapati, 2008), but this does only cover a small part of the full value contribution to free e-service providers.

In particular, specialized social networks like outdoor communities rely on data and the enrichment of data points as core resources: “Our value consists of a database of destinations, which is as comprehensive as possible. We connect to different [external] data sources, but our database will never be complete. Therefore, we have to permanently incentivize our members to supply destinations, photos, etc.” (M82). Similarly, GPS data points generated by customers that are used for improving the routing algorithm constitute an important asset for an outdoor community (S16). In addition, data represent an important enabler for harnessing the monetary value of attention. Better ad targeting and personalized, individualized offerings can enhance ad effectiveness (Iyer et al. 2005). Consequently, free online platforms become more attractive for advertisers and can increase revenues by offering data-driven targeted advertising (Schumann et al., 2014). As one manager emphasized, “without exact profile data, our advertising wouldn’t be better than in any other network” (F59). Free e-service providers can also use data provided by nonpaying customers for analytics and market research—both internally and for third parties. For example, a real-estate marketplace in our sample consolidates the data from all listings to calculate a property value index, which users can access for a small fee (U22).

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

2.5 Discussion

Building on a literature review and an interview study with managers of free e-services, this study provides a comprehensive overview of NMCVCs in the free e-service industry. Our findings contribute to marketing theory and practice in at least five ways. First, we identify two new dimensions of NMCVCs, namely attention and data, which have not previously been discussed in research on customer value. Both attention and data are core constituents of many free e-service business models but also play a role outside the free e-service domain. For example, media firms such as TV channels or newspapers can either be financed by advertising revenue, by direct payment from the viewers, or by both in combination (Kind, Nilssen, & Sørgard, 2009). Using attention for cross- and upselling seems to be an even more common phenomenon. Similarly, the value of data provided by customers is also not limited to e-services, even though the Internet facilitates data collection (Chen et al., 2012). Hence, our findings do not only advance knowledge on the value of nonpaying customers in e-services but also contribute to research on customer value in general.

Second, the identification of attention and data as new NMCVC dimensions contributes to customer engagement research by exploring the definitional boundaries of CEBs. Although the overall scope of CEBs is still under discussion, there is a broad consensus that CEBs are voluntary behaviors with a brand or firm focus resulting from motivational drivers (Brodie et al., 2011; Jaakkola & Alexander, 2014; Kumar, Aksoy et al., 2010; van Doorn et al., 2010). Both attention and data seem to be of a semi-motivational nature, such that they only partly comply with the existing definition of CEBs: On the one hand, using many free e-services without providing attention and data is not possible or requires special measures, such as using tracking protection or installing ad-blocking software, which suggests a nonmotivational nature. Prior research shows that even incidental and involuntary exposure to advertising can change consumer attitudes (Janiszewski, 1993) and therefore is of value to free e-service providers. On the other hand, customers actively argue in favor of advertising, referring to reciprocity arguments—supporting the existence of motivational drivers: “Sometimes there are discussions on annoying ads, for example, layer formats, which can actually be annoying. Many users then start fretting, but others try to calm them down; the platform is for free, and somehow they just have to make money” (I68). Similarly, data provision, especially for profile data, is often voluntary and reciprocity appeals can increase the willingness to provide personal information for targeted advertising (Schumann et al., 2014). The fact that, according to the existing definition, the same NMCVC, such as watching an advertisement, can qualify as CEB or not—depending on the customer’s psychological state, provides several opportunities for future research and theory refinement: What are the definitional boundaries between motivational and nonmotivational behaviors towards the firm? For instance, does not using options to reduce NMCVCs, like not skipping an ad, qualify as CEB? What are the implications for free e-service providers if data or attention are provided voluntarily? How does creating awareness for previously nonmotivational NMCVCs influence other CEBs?

Third, we contribute to research on the emerging free e-service sector (Anderson, 2009; Bryce et al., 2011; Casadesus-Masanell & Zhu, 2013) by carving out the dimensions and roles of NMCVCs in free e-services. Besides confirming WOM, co-production, and network effects as important NMCVCs in the free e-service industry and identifying attention and data as additional dimensions, we extend existing knowledge on co-production and network effects. Whereas the value and characteristics of WOM seem comparable for paying and nonpaying customers, we identify three subtypes of co-production that are especially important in the free e-service sector: co-production of content, co-management, and brand co-creation. In addition, our interview study approach covering a broad range of free e-service business models allows us to distinguish three generic drivers for network effects. The network value of customers of free e-services is determined by their fit to other customers, their reputation, and their degree of interconnectedness. Although fit and interconnectedness in particular have been identified in prior research (Iyengar et al., 2011; Katona et al., 2011; Nitzan & Libai, 2011; Vock et al., 2013), we are the first to apply them consistently for intramarket and cross-market network effects.

Fourth, our research on free e-services extends the discussion on value co-creation in networked environments in SDL (Lusch & Vargo, 2006; Vargo & Lusch, 2008). Free e-services seem to undermine the generalizability of selected SDL foundational premises, as provider and customer roles can vary (Kuppelwieser et al., 2013): For example, an online community such as YouTube involves several customers, as users and/or resource integrators, resulting in complex network relationships of value creation. Kuppelwieser et al. (2013, p. 319) therefore call for a reexamination of the SDL foundational premises in order to develop a "uni-applicable theory" encompassing the e-service sector. By providing a comprehensive analysis of value creation in free e-services, our research constitutes an important step for a deeper discussion of SDL in the context of free e-services.

Fifth, conceptualizing NMCVCs and linking them to business outcomes for the firm can change managerial perceptions and increase awareness of the NMCVCs that nonpaying customers provide. Many of the managers we interviewed initially did not view their often anonymous and nonpaying users as customers, "because customers always pay" (B22). Our findings enable managers to gain a more nuanced understanding of NMCVCs and to develop their customer concept. Comprehending nonmonetary value contributions is an essential first step for e-service providers to establish and manage customer relationships with their nonpaying customer base: "Our biggest opportunity is to build real customer relationships" (B152).

2.6 Outlook

Several limitations of our study provide fruitful avenues for further research. First, our work is conceptual and qualitative in nature. An empirical validation could reconfirm our findings on a larger scale and create a link between managerial perceptions of NMCVCs and performance measures for the business success of free e-service providers. Our research also yielded some indications that the valuation and importance of NMCVCs vary along different business models and company stages. It would be worthwhile to determine whether empirical results confirm this observation.

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

Third, our research only touches upon the question of how to measure NMCVCs in free e-services. The measurement of NMCVCs emerged as an important challenge in our interviews. While all firms in our sample monitor online customer behavior using tracking and analytics tools, none of them measures nonmonetary customer value on an individual “micro level” (N86). Additional studies need to find ways to identify actual individual-level customer contributions, then measure and integrate them in customer value and customer equity calculations. Such metrics would not only be relevant for free e-services but can also help managers of other firms to better understand the value of their customers.

Last but not least, we focused on the free e-service industry, which—as an important pillar of the Internet economy—constitutes an interesting research object by itself. However, as an extreme case without any monetary revenues from end customers, the free e-service industry may also be regarded as a magnifying glass that highlights important new aspects of NMCVCs in general. Hence, further research should investigate the applicability of our findings—especially regarding the newly identified dimensions of attention and data—in a broader context, using the free e-service industry as a starting point.

3 Mapping the Customer Journey: A Graph-Based Framework for Online Attribution Modeling

Eva Anderl, Ingo Becker, Florian von Wangenheim, Jan H. Schumann

Advertisers employ various channels to reach consumers over the Internet but often do not know to what degree each channel actually contributes to their marketing success. This attribution challenge is of great managerial interest, yet approaches to it developed in marketing academia have not found wide application in practice. To increase practical acceptance, the authors introduce a graph-based framework to analyze multichannel online customer path data as first- and higher-order Markov walks. According to a comprehensive set of criteria for attribution models, embracing both scientific rigor and practical applicability, four model variations are evaluated on four, large, real-world data sets from different industries. Results indicate substantial differences to existing heuristics such as "last click wins" and demonstrate that insights into channel effectiveness cannot be generalized from single data sets. The proposed framework offers support to practitioners by facilitating objective budget allocation and improving team decisions, and allows for future applications such as real-time bidding.

3.1 Introduction

Online advertising is essential to many industries' promotional mix (Raman et al., 2012). In the United States, online marketing accounts for more than 20% of overall marketing spending, amounting to $42.8 billion in 2013 (PriceWaterhouseCoopers, 2014). Advertisers use a variety of online marketing channels,[5] including paid search and display marketing, as well as e-mail, mobile, and social media advertising to reach consumers. This proliferation of channels makes budget allocation decisions increasingly complex (Raman et al., 2012). Furthermore, consumers may be exposed to advertisements through various channels, yet advertisers lack transparency about the degree to which each channel or campaign contributes to their companies' success.

[5] In this study, we use the term "online marketing channels" to cover different online marketing instruments, including search engine advertising, display, or social media advertising.

Marketing executives thus call for performance measures of the contributions of each online marketing channel (Econsultancy, 2012a; Ramsey, 2009). The challenge of attributing credit to different channels (Neslin & Shankar, 2009) involves finding ways to measure "the partial value of each interactive marketing contact that contributed to a desired outcome" (Osur, 2012, p. 3). To award such credit, many advertisers apply simple heuristics, such as "last click wins," such that the value gets attributed solely to the marketing channel that directly preceded the conversion (Econsultancy, 2012a; The CMO Club & Visual IQ, Inc., 2014), and any prior customer interactions are disregarded.

Modern technological advancements enable recording of customer journey data though, enabling new ways to address the attribution problem (Bucklin & Sismeiro, 2009). In our definition, an online customer journey includes all advertising exposures for an individual customer over all online marketing channels preceding a (potential) purchase decision.[6] As a result, the market for such tracking technologies has gained momentum (Osur, 2012; Tucker, 2012), such that the use of attribution models has doubled since 2008, and nearly 75% of marketers believe that attribution measures can improve the allocations of their budgets across channels, which might enhance their return on investments as well (Econsultancy, 2012a; Riley, 2009). Although some software tool providers now offer multitouch attribution solutions,[7] last and first click wins heuristics remain among the most widely used attribution methods in practice (Econsultancy, 2012a). Furthermore, even the multitouch attribution tools used in practice largely rely on simple heuristics, such as weights predefined by an advertiser, which assign a particular weight to each position or channel over the course of successful customer journeys. Other popular heuristics include linear attribution approaches, which split the contribution evenly across all channels included in a successful journey, and time-decay methods, for which contacts closer to the conversion receive more credit (Econsultancy, 2012a, 2012b; Osur, 2012). Only three major vendors offer statistical or algorithmic attribution methodologies (Osur, 2012), but their mechanisms remain

[6] Similar concepts have been referred to as the buying funnel (Jansen and Schuster, 2011), purchasing funnel (Jordan, Mahdian, Vassilvitskii, & Vee, 2011), or the consumer decision journey (Edelman, 2010).

[7] Examples of companies used in this context include, but are not limited to, Adclean, Adometry, Atlas, C3 Metrics, ClearSaleing, Coremetrics (IBM), Google, Theorem, Trueeffect, Visual IQ, Icrossing, and [x+1].

publicly unavailable and irreproducible (Dalessandro, Perlich, Stitelman, & Provost, 2012).

In turn, despite its practical relevance, the attribution problem only recently has become a focus for marketing researchers (Abhishek et al., 2012; Berman, 2013; Haan et al., 2013; Kireyev et al., 2013; Li & Kannan, 2014; Xu et al., 2014), likely related to the increasing availability of high-quality clickstream data. However, to the best of our knowledge, sophisticated attribution approaches have not found wide application in practice. This gap, such that academically developed methods do not find their way into managerial applications, is a widely lamented problem (Reibstein, Day, & Wind, 2009). Acceptance and adaption of marketing models demands more than analytical rigor (Lehmann, McAlister, & Staelin, 2011; Little, 1970; Wübben & Wangenheim, 2008); managers hesitate to base their decisions on mechanisms whose results are not available when they need them (Lodish, 2001) or if they do not understand how the insights are generated (Lilien, Roberts, & Shankar, 2013; Little, 1970, 2004). Thus, though the available academic frameworks are appealing and innovative, a practice-oriented attribution approach also needs to fulfill important criteria for managerial acceptance, such as ease of interpretation, versatility, or algorithmic efficiency.

In response, we introduce a novel, practice-oriented attribution framework based on Markovian graph-based data mining techniques. Using four large, real-world data sets, we evaluate it according to a set of criteria for attribution models, building on existing research on managerial decision models (Lehmann et al., 2011; Lilien, 2011; Little, 1970, 2004; Lodish, 2001). We compare our suggested framework against existing attribution approaches and apply it to a real-life system implemented at a German multichannel tracking provider. Thus, we extend existing discussions of attribution and contribute to marketing theory and practice in a number of ways.

First, we propose a novel framework for analyzing multichannel online customer path data. We model and analyze individual-level multichannel customer journeys as first- and higher-order Markov graphs, using a property we call removal effect to determine channel contributions. Our approach thus provides a practice-oriented alternative to widely used, often misleading attribution heuristics applied by online marketers. Second, we contribute new insights into online marketing effectiveness in a multichannel setting. We find that higher-order models outperform the first-order, “memory-free” Markov graphs in their predictive accuracy. This proof adds to the existing evidence that one-click heuristics, such as last click wins, are not sufficient to capture the contributions of online channels. In line with prior research, we find that certain channels such as display are undervalued by existing attribution heuristics (Abhishek et al., 2012; Li & Kannan, 2014), whereas other channels like paid search tend to be overestimated. With our four, large-scale data sets across three different industries, we enable cross-industry comparisons and find that insights on channel effectiveness cannot be generalized from results obtained from a single data set. This finding enhances the need for an easily applicable, versatile attribution framework. Third, by developing a set of evaluation criteria, we reduce the thresholds for applying and selecting attribution techniques in managerial practice (Econsultancy, 2012a), foster standardization and cross-industry acceptance (Dalessandro et al., 2012), and improve fairness in evaluating the contribution of online marketing channels (Dalessandro et al., 2012). Fourth and finally, our study responds to research requests to develop marketing impact models and techniques based on individual-level, single-source data (Rust, Lemon, & Zeithaml, 2004) and provides a new perspective on analyzing path data in marketing (Hui, Fader, & Bradlow, 2009).

From a managerial perspective, our research provides solutions to several explicit problems that practitioners confront. It facilitates an objective and independent logic for deriving budget optimization processes and strategic decisions, such as channel selection. The framework can update the mental models of decision makers, by building up the expertise of marketing managers. Because it is purely data driven, it affects organizations such that it reduces hierarchies and consecutively improves team decisions (Lilien, 2011). The versatility of our framework makes it suitable across industries and marketing contexts and allows for future applications.

The rest of this article is organized as follows. We first position our research in the context of existing literature and develop multiple criteria that a successful attribution model should fulfill to be both scientifically valid and applicable in practice. After a description of our clickstream data, we introduce our framework, including several model variations, and present the evaluation results in comparison to existing attribution approaches. Next, we discuss the impacts of our research for marketing theory and practice. We conclude with an overview of limitations and directions for further research.

3.2 Research Background

3.2.1 Research on Attribution Modeling

Academic research on attribution is still scarce (Raman et al., 2012; Tucker, 2012) but can build on prior studies pertaining to online advertising effectiveness. Most existing research focuses on single channels, such as search (Ghose & Yang, 2009; Rutz & Bucklin, 2011; Yang & Ghose, 2010) or display (Braun & Moe, 2013; Goldfarb & Tucker, 2011). Studies comparing the short- and long-term effectiveness of different online advertising channels based on aggregate data relate to the attribution problem (Breuer & Brettel, 2012; Breuer, Brettel, & Engelen, 2011), yet they do not attempt to award credit for conversions. Jordan et al. (2011) examine allocation decisions for publishers, using multiple attribution approaches, and derive optimal allocation and pricing rules for publishers selling advertising slots. In a study of the economic welfare consequences of the use of attribution technologies, Tucker (2012) finds evidence for more conversions at lower costs, due to the ability to systematically substitute towards selected campaigns across advertising platforms. These findings underline the potential impact of attribution on marketing effectiveness, though the attribution methodology they use remains undisclosed and not subject to examination. Practice-oriented literature on attribution mainly highlights the relevance of the topic or summarizes ongoing industry activities, without providing methodological details (Chandler-Pepelnjak, 2008, Econsultancy, 2012a, 2012b; Lovett, 2009; Osur, 2012; Riley, 2009).

Furthermore, we know of few academic studies that address the online attribution problem: Shao and Li (2011) introduce two attribution approaches, a bagged logistic regression model and a simple probabilistic model. Building on their work, Dalessandro et al. (2012) propose a more complex, causally motivated attribution methodology based on cooperative game theory. Based on a set of simulated campaign data they find that advertisers tend to assign credit to conversions that are driven by the users' volition to convert rather than on the factual influence of the advertisement. Focusing on the interplay between advertisers and publishers, Berman (2013) evaluates the impact of different incentive schemes and attribution methods on publishers' propensity to show ads and the resulting profits of advertisers. He introduces an analytical model based on Shapley value, similar to the model proposed by Dalessandro et al. (2012), and compares it to the last click wins heuristic. Abhishek et al. (2012) suggest a dynamic hidden Markov model (HMM), based on individual consumer behavior, that captures a consumer's deliberation process along typical stages of the purchase funnel: dormant, awareness, consideration, and conversion. They find that different channels, e.g. display and search ads, affect the consumers in different states of their decision process. For example, display ads usually impact consumers early in the decision process, moving them from a state of dormancy to awareness or consideration. Li and Kannan (2014) propose a Bayesian model to measure online channel consideration, visits, and purchases using individual conversion path data and validate it in a field experiment. They use the estimated carryover and spillover effects to attribute conversion credit to different channels and find that these channels' relative contributions are significantly different from last click wins. By means of a mutually exciting point process model, Xu et al. (2014) calculate average conversion probabilities for different online advertising channels, showing that the conversion rate measure underestimates the effect of display ads compared to search ads. A multivariate time-series model based on aggregate data by Kireyev et al. (2013) analyzes attribution dynamics for display and search advertising. They derive spillover effects from display towards search conversion; however, display ads also increase search clicks, thereby increasing costs for search engine advertising. Finally, Haan et al. (2013) propose a structural vector autoregression (SVAR) model, also based on aggregate data, to determine the effectiveness of various offline and online advertising channels. Marketing effectiveness differs depending on the locus of communication initiation, with customer-intiated contacts significantly outperforming firm-initiated contacts.

3.2.2 Criteria for Attribution Modeling

Putting academic marketing models to work in practice is challenging, because the most complex model is not necessarily the one that will affect an organization's productivity (Little, 1970; Lodish, 2001). In the following, we therefore conceptualize marketing attribution modeling with a catalogue of six criteria that reflect scientific rigor as well as aspects relevant to the implementation in practice. We build on prior research into the acceptance of marketing decision models (Leeflang & Wittink, 2000; Lilien, 2011; Little, 1970, 1979, 2004; Lodish, 2001; Reibstein et al., 2009) and connect them with criteria previously discussed in the context of attribution modeling (Dalessandro et al., 2012; Shao & Li, 2011). Table 3 provides an overview of the six criteria we propose and their relation to prior literature.

Table 3

Evaluation Criteria for Attribution Models—Study 2

Criterion	Definition	Relation to prior research: Studies	Relation to prior research: Description
Objectivity	Models must be able to assign credit to individual channels or campaigns in accordance with their factual ability to generate value, such as contributing to conversions or increasing revenues.	Lilien (2011)	Models should allow for computing the relative impact of decision variables and enable objectivity in evaluating decisions options.
		Dalessandro et al. (2012)	Attribution systems should reward an individual channel in accordance with its ability to affect the likelihood of conversion (fairness).
Predictive accuracy	Models should be able to predict conversion events correctly.	Lodish (2001)	Predictive validity is important to persuade managers of a model's credibility.
		Shao and Li (2011)	Attribution models should have high accuracy in predicting active or inactive users (accuracy).
Robustness	Models should deliver stable and reproducible results if they run numerous times.	Little (1970, 2004)	Models should be robust to avoid bad, unstable results.
		Shao and Li (2011)	Attribution models should deliver stable estimates (variability).
Interpretability	Model structure should be transparent to all stakeholders with reasonable effort, and the results should be interpretable with relative ease.	Little (1970)	Model users should be able to transfer model results directly into managerial decisions.
		Little (1970, 2004)	Models should be simple and easy to communicate.
		Little (1970); Lodish (2001); Lilien (2011)	Models should be easy to interpret, because managers refuse to apply black box approaches.
		Dalessandro et al. (2012)	An attribution system needs to be accepted "by all parties with material interest" based on its "statistical merit" and the "intuitive understanding" of the system's components.
Versatility	Versatility combines adaptability and ease of control. Adaptability is the capability to incorporate new information that becomes available over time. Ease of control enables users to adjust inputs to fit company-specific requirements and derive appropriate outputs.	Little (1970)	Models should be "adaptive" and "easy to control." "Adaptive" describes the capability to update the model as soon as new information become available; "easy to control" enables the user to adjust inputs to modify outputs.
		Lodish (2001)	Models should deliver an adequate level of aggregation to achieve acceptance by managers.
Algorithmic efficiency	The speed of computing model outputs when they are requested.	Little (1970, 2004)	Model structures should be complete in relevant issues and able to handle many phenomena without being bogged down.
		Lodish (2001)	Models need to provide results as soon as managers require them to be applicable in practice.
		Archak, Mirrokni, and Muthukrishnan (2010)	As a basic precondition for practical purposes, a methodology must be able to handle large data volumes fast and efficiently.

Marketing decision models should enable the computation of the relative impacts of different decision variables and enable *objectivity* in budget decisions (Lilien, 2011). In the case of attribution, models need to be able to assign credit to individual channels or campaigns in accordance with their factual ability to generate value, such as by contributing to conversions or increasing revenues (Dalessandro et al., 2012). Although objectivity seems to be an obvious criterion, most models applied in practice break this rule. For example, models that condense user journeys to one click (e.g., first- or last-click heuristics) omit any additional marketing contacts, and more complex models based on predefined weights by the advertiser fail to attribute credit fairly across channels.

Although attribution primarily takes a retrospective view, attribution models should be able to correctly predict conversion events (Shao & Li, 2011). In addition to ensuring scientific rigor, this classification helps to persuade managers of the model's credibility (Lodish, 2001). We therefore introduce *predictive accuracy* as a second criterion.

Robustness is another important metric to evaluate model fitness (Little, 1970, 2004; Shao & Li, 2011). Robustness conveys the ability of a model to deliver stable and reproducible results if the model runs multiple times (Little, 1970) and is indispensable for sustainable budget decisions. While the focus of existing research on digital marketing has been on predictive modeling, a stable interpretation of the influence of each user interaction is highly important for attribution models (Shao & Li, 2011).

To ensure managerial acceptance, models need to be simple and easy to communicate (Little, 1970, 2004), which we summarize as *interpretability*. Simplicity comprises the intuitive understandability of a model "by all parties with material interest" (Dalessandro et al., 2012, p. 2). Managers should be capable of adjusting inputs and understanding outputs with relative ease. The interpretability of the results is of utmost importance for practical acceptance, because managers often refuse to use black box approaches that conceal how they work or how they generate results (Lilien, 2011; Little, 1970; Lodish, 2001).

Little (1970) posits that models should be adaptive and easy to control, which we combine to *versatility*. Adaptability encompasses the capability of incorporating new information that becomes available over time, which is particularly critical in rapidly changing environments (Leeflang & Wittink, 2000). In the online environment, the set of available channels is constantly evolving (Evans, 2009). An attribution framework therefore should be able to include varying channels and should easily be extended toward innovative forms of advertising. Furthermore, a model should allow for different aggregation levels, because managers are likely to neglect results if the measures are not accessible at the right level of aggregation (Lodish, 2001).

Finally, we introduce *algorithmic efficiency*, or the speed with which the model computes outputs when requested, as a sixth criterion. With recent advances in online tracking technologies, clickstream data sets can be of tremendous size, comprising millions of clicks or even billions of impressions (Bucklin & Sismeiro, 2009), posing new challenges for algorithmic efficiency. To be suitable for practical purposes an attribution methodology must be able to handle these volumes efficiently, because practitioners will not apply results that are not available when required (Lodish, 2001).

Using these criteria, derived both from research on marketing model acceptance and recent work on attribution modeling, we provide a comprehensive framework to evaluate attribution models that includes requirements from both academia and practice. Next, we connect the evaluation criteria we have identified to the existing literature on attribution modeling.

3.2.3 Connecting Criteria for Attribution Modeling and Prior Research

Only three of the existing academic approaches (Abhishek et al., 2012; Li & Kannan, 2014; Xu et al., 2014) *objectively* assign credit to each individual contact in accordance with their factual ability to generate value. In contrast, the approaches by Shao and Li (2011) and Dalessandro et al. (2012) neglect the frequency of channels in a customer journey; models based on aggregate data ignore the influence of individual contacts (Haan et al., 2013; Kireyev et al., 2013). With the exception of Berman (2013), all of the cited studies evaluate *predictive accuracy* using a variety of measures, such as log-likelihood (Abhishek et al., 2012; Li & Kannan, 2014), mean absolute percentage error (Haan et al., 2013; Li & Kannan, 2014), or the sum of squared errors (Xu et al., 2014). The HMM proposed by Abhishek et al. (2012) outperforms a simple logit model on its root mean squared error and log-likelihood. Yet no overall comparison of predictive accuracy for the existing approaches is possible, because the data sets used and implementation details are not publically available, and the measures used differ across studies. Only Shao and Li (2011) evaluate *robustness,* which they call variability. No other studies explicitly analyze robustness, though Li and Kannan (2014) provide additional validation using a field experiment and Xu et al. (2014) use out-of-sample validation. Using standard statistical methods, the approaches adopted by Shao and Li (2011), Dalessandro et al. (2012), and Berman (2013) are relatively easy to interpret, even without profound knowledge of marketing modeling techniques. The degree of complexity of the other models likely makes it difficult for practitioners to follow their calculation logic, leading to limited *interpretability*. In addition, though some models are highly flexible (Berman, 2013; Dalessandro et al., 2012; Shao & Li, 2011; Xu et al., 2014), the *versatility* of other approaches is limited by their explicit assumptions about the customer decision process and channel characteristics (Abhishek et al., 2012; Li & Kannan, 2014), as well as their restrictions regarding specific channels. For example, Haan et al. (2013) do not include channels with performance-based payment models, such as affiliates, to avoid endogeneity. No authors mention *algorithmic efficiency*, possibly because some of the samples used were relatively small, such that efficiency considerations became less relevant. As reliable statements about algorithmic efficiency are hard to make from an outside perspective, we deliberately choose not to evaluate this criterion.

Overall, this application of our evaluation criteria on the existing literature on attribution modeling, which we summarize in Table 4, indicates important progress from an academic perspective but also shows that practical considerations are often not reflected. We therefore seek to develop a model that meets all of the suggested criteria and evaluate it using real-life data sets.

Table 4

Existing Research on Attribution Modeling—Study 2

		Evaluation criteria					
Study	Methodology	Objectivity	Predictive accuracy[a]	Robustness	Interpret-ability	Versatility	Algorithmic efficiency
Shao and Li (2011)	(1) Bagged logistic regression (2) Simple probabilistic model	No; frequency of contacts and positions not considered	Yes	Yes	Yes	Yes	Not available
Dalessandro et al. (2012)	Causally motivated methodology based on cooperative game theory (Shapley value) combined with logistic regression	No; frequency of contacts not considered	Yes	Not measured	Yes	Yes	Not available
Abhishek et al. (2012)	Dynamic HMM	Yes	Yes	Not measured	Limited	Limited; assumptions on channels and structure of decision process	Not available
Berman (2013)	Analytical model based on cooperative game theory (Shapley value) combined with OLS regression	No; frequency of contacts not considered	Not measured	Not measured	Yes	Yes	Not available
Haan et al. (2013)	Structural vector autoregression	No; not based on individual data	Yes	Not measured	Limited	Limited; not suited for performance-based channels (e.g. affiliate)	Not available
Kireyev et al. (2013)	Multivariate time-series model (persistence modeling)	No; not based on individual data	Yes	Not measured	Limited	Limited; application based on 2 channels (display and SEO)	Not available

		Evaluation criteria					
Study	Methodology	Objectivity	Predictive accuracy[a]	Robustness	Interpret-ability	Versatility	Algorithmic efficiency
Li and Kannan (2014)	Bayes	Yes	Yes	Not measured; validation by field experiment	Limited	Limited; assumptions on channels and structure of decision process	Not available
Xu et al. (2014)	Mutually exciting point process model	Yes	Yes	Out-of-sample validation	Limited	Yes	Not available
Our study	Markov graphs (first- and higher-order)	Yes	Yes	Yes	Yes	Yes	Yes

[a]This table only indicates if predictive accuracy is evaluated in the respective study. The data sets used and implementation details are not publically available, and the measures vary, so a comparison of predictive accuracy across studies is not possible.

3.3 Data

Our research is based on four clickstream data sets provided by online advertisers, in collaboration with a multichannel tracking provider. Clickstream data record each user's Internet activity and thus trace the navigation path he or she takes (Bucklin & Sismeiro, 2009). For each visit to the advertiser's website during the observation period, the data include detailed information about the source of the click and an exact timestamp. Clicks either represent a direct behavioral response to an advertising exposure or result from the user entering the advertiser's uniform resource locator (URL) directly into the browser, so these sources comprise all online marketing channels, as well as direct type-ins. We also know for each visit whether it was followed by a conversion, in this case a purchase transaction. We use this information to construct customer journeys that describe the click pattern of individual consumers across all online marketing channels and their purchase behavior. Thus, we not only track successful journeys ending with a conversion but also journeys that never lead to a conversion, within a timeframe of 30 days of the last exposure.

The data collection occurs at the cookie-level, such that we identify individual consumers—or more accurately, individual devices. The use of cookie data suffers several limitations, such as an inability to track multidevice usage or bias due to cookie deletion (Flosi, Fulgoni, & Vollman, 2013; Rutz, Trusov, & Bucklin, 2011), yet cookies remain the industry standard for multichannel tracking (Tucker, 2012). In contrast with prior research (Breuer & Brettel, 2012; Breuer et al., 2011; Lohtia, Donthu, & Yaveroglu, 2007), we use cross-sectional field data, which allow us insights into the interaction of individual advertising exposures. We do not include information on offline marketing channels, because measuring individual-level exposure to multiple offline media proves highly difficult in practice (Danaher & Dagger, 2013).

The advertisers that provide the data sets for this study operate in different industries: fashion retail, luggage retail, and travel. All are pure online players, so we can exclude online/offline cross-channel effects (Wiesel, Pauwels, & Arts, 2011). Each data set includes a minimum of 405,000 journeys per advertiser. Their average length is 1.3–2.5 contacts, and between 0.9% and 2.0% of all journeys lead to a successful conversion. All advertisers included in the evaluation distinguish seven or eight different online channels, though the channels used differ partly across firms. Search engine advertising (SEA), search engine optimization (SEO), affiliate, and newsletter appear in all four data sets. Other channels used by the advertisers include display, price comparison, social media advertising, and retargeting. In Table 5, we present detailed descriptions of our data sets.

Table 5

Descriptions—Study 2

Description	Data set 1	Data set 2	Data set 3	Data set 4
Industry	Travel	Fashion retail	Fashion retail	Luggage retail
Number of different channels	8	8	7	7
Number of clicks	1,478,359	1,639,467	1,125,979	615,111
Number of journeys	600,978	1,184,583	862,112	405,339
Thereof with length ≥ 2	206,519	170,914	142,039	105,031
Thereof with length ≥ 5	48,344	30,095	12,416	11,475
Journey length	2.46 (8.860)	1.38 (1.916)	1.31 (1.238)	1.52 (4.587)
Number of conversions	9,860	10,153	16,200	8,115
Journey conversion rate	1.64%	0.86%	1.88%	2.00%

Note. Standard deviations are in parentheses.

3.4 Model Development

We propose a graph-based Markovian framework to analyze customer journeys and derive an attribution model, adapting an approach proposed by Archak, Mirrokni, and Muthukrishnan (2010) in the context of search engine advertising. Markov chains are probabilistic models that can represent dependencies between sequences of observations of a random variable. They have a long history in marketing (Styan & Smith, 1964) and have been used frequently to model customer relationships (Homburg, Steiner, & Totzek, 2009; Pfeifer & Carraway, 2000). Other applications include advertising frequency decisions (Bronnenberg, 1998) and brand loyalty (Che & Seetharaman, 2009).

In our model, we represent customer journeys as chains in directed Markov graphs.[8] A Markov graph $M = \langle S, W \rangle$ is defined by a set of states:

$$S = \{s_1, \dots, s_n\}. \quad (1)$$

and a transition matrix *W* with edge weights

$$w_{ij} = P(X_t = s_j | X_{t-1} = s_i), 0 \leq w_{ij} \leq 1, \sum_{j=1}^{N} w_{ij} = 1 \; \forall \, i \quad (2)$$

Using this graph-based approach allows us to represent and analyze customer journeys in an efficient way as the size of the final graph does not depend on the number of journeys in the data set but only on the number of states.

3.4.1 Base Model

Customer journeys contain one or more contacts across a variety of channels. In the base model, each state s_i corresponds to one channel. If an advertiser employs three different channels C1, C2, and C3 in his online marketing mix, the model would include three states C*1*, *C2*, and *C3*.[9] Additionally, all graphs contain three special states: a *START* state that represents the starting point of a customer journey; a *CONVERSION* state representing a successful conversion; and an absorbing *NULL* state for customer journeys that have not ended in a conversion. The full set of states S in our example would hence look as follows: S = {*START*, *CONVERSION*, *NULL*, *C1*, *C2*, *C3*}.

The transition probability w_{ij} in the base model corresponds to the probability that a contact in channel i is followed by a contact in channel j. For the first channel in each journey, we add an incoming connection from the *START* state. If a customer journey ends in a conversion, we connect the state representing the last channel in the journey to the *CONVERSION* state, otherwise it leads to the *NULL* state. For modeling reasons, we always add a connection from the *CONVERSION* state to the *NULL* state. Cycles in the graph are possible, such as when a sequence of two identical channels appears in a customer journey. Figure 2 shows an exemplary Markov graph based on three customer journeys. Figure 3 provides a graphical structure of the simple model for data set 1.

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[8] Called adgraphs by Archak, Mirrokni, and Muthukrishnan (2010).

[9] As we do not make any assumptions on the channels used, we employ dummy channels in our examples. In practice, the set of channels—and thus the set of states—depends on the actual channels used by the advertiser.

Figure 2

Exemplary Markov Graph—Study 2

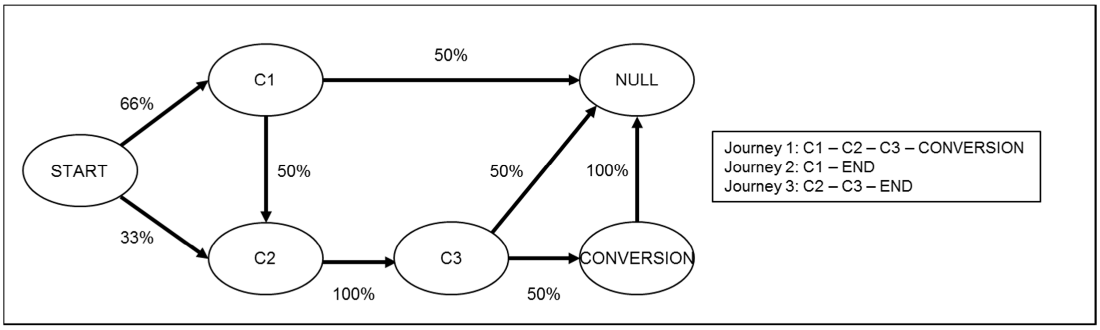
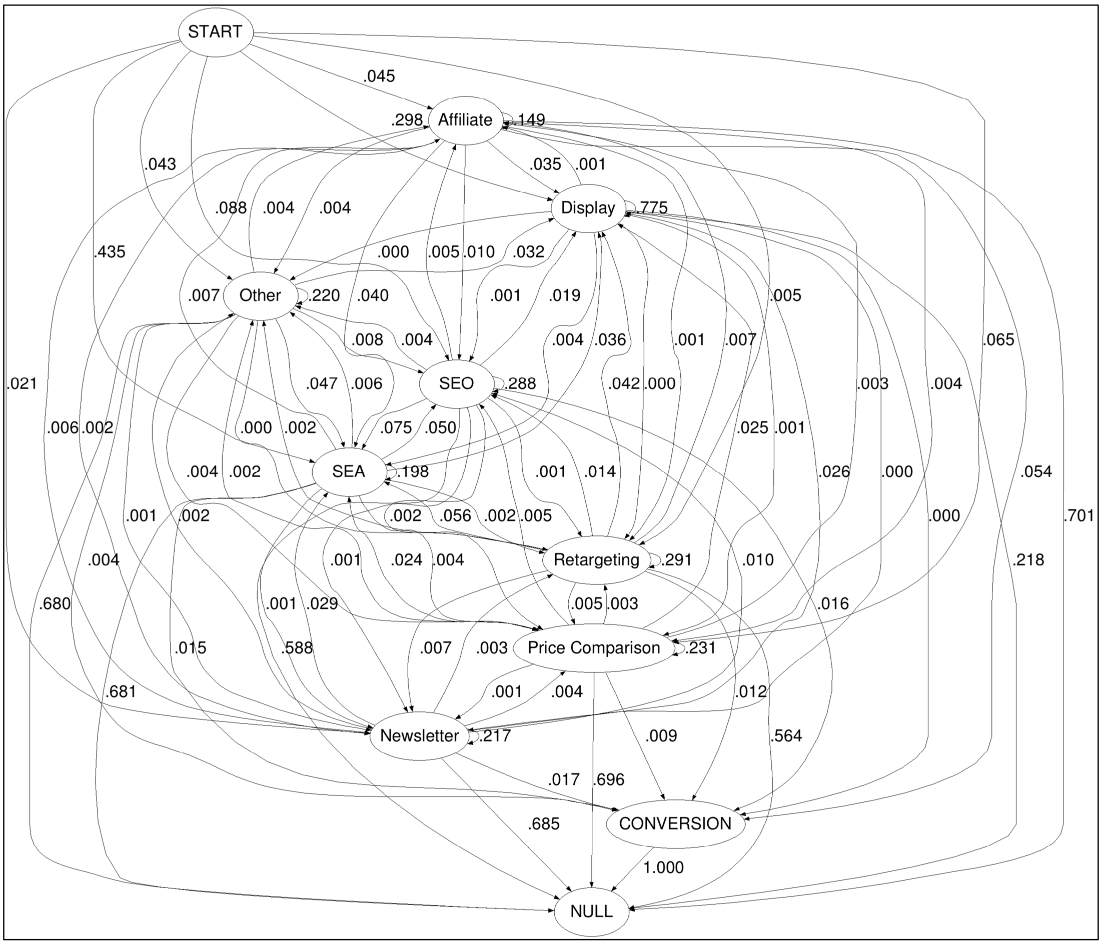


Figure 3

Markov Graph for Data Set 1 (Base Model)—Study 2



3.4.2 Higher-Order Models

Markovian models, as used by Archak et al. (2010), suggest that the present only depends on the first lag and do not incorporate previous observations. Because prior research suggests that clickstreams should not be regarded as strictly Markovian though (Chierichetti, Kumar, Raghavan, & Sarlós, 2012; Montgomery, Li, Srinivasan,

& Liechty, 2004), we introduce alternative higher-order models, in which the present depends on the last k observations. Transition probabilities thus can be defined as follows:

$$P(X_t = s_t | X_{t-1} = s_{t-1}, X_{t-2} = s_{t-2}, \dots, X_1 = s_1) = P(X_t = s_t | X_{t-1} = s_{t-1}, X_{t-2} = s_{t-2}, \dots, X_{t-k} = s_{t-k}). \quad (3)$$

For our implementation, we exploit the knowledge that a Markov chain of order k, over some alphabet A, is equivalent to a first-order Markov chain over the alphabet A_k of k-tuples. States in higher-order models therefore include k-tuples of states in the first-order models. Unfortunately, the number of independent parameters increases exponentially with the order of the Markov chain and quickly becomes too large to be estimated efficiently with real-world data sets (Berchtold & Raftery, 2002). Considering these implementation issues in relation to algorithmic efficiency, we limit our analyses to Markov chains of a maximum order of four.

3.4.3 Removal Effect

The representation as Markov graphs allows identifying structural correlations in the customer journey data that can be used to develop an attribution model. Archak et al. (2010) propose a set of *ad factors* to capture the role of each state, such as *Eventual Conversion(s_i)*, i.e. the probability of reaching conversion from a given state s_i. *Visit(s_i)* is the probability of passing s_i on a random walk beginning in the *START* state. For attribution modeling, we propose using the ad factor *Removal Effect(s_i)*, defined as the change in probability of reaching the *CONVERSION* state from the *START* state when we remove s_i from the graph. As *Removal Effect(s_i)* reflects the change in conversion rate if the state s_i was not present, it is well suited to measure the contribution of each channel (or channel sequence). Using the assumption that all incoming edges of the state s_i that we remove are redirected to the absorbing *NULL* state, *Removal Effect(s_i)* is equivalent to the multiplication of *Visit(s_i)* and *Eventual Conversion(s_i)*.[10] The removal effect can thus be efficiently calculated using matrix multiplication or applying local algorithms provided by Archak et al. (2010).

Removal Effect(s_i) can take values between 0 and the total conversion rate. However, as most existing attribution heuristics use percentage values, we report removal effects per state as percentages of the sum of all removal effects (excluding

[10] For a proof, see Archak et al. (2010).

the special states START, CONVERSION, and NULL), when comparing our results to other models. Higher-order models allow us to calculate removal effects for states representing channel sequences; in addition, we also aggregate the mean values for each channel to get information on a channel level.

3.5 Results

We evaluate our models according to the previously established criteria—objectivity, predictive accuracy, robustness, interpretability, versatility, and algorithmic efficiency—and compare our results against existing attribution heuristics.

3.5.1 Application of Evaluation Criteria

The graph-based framework we propose satisfies the *objectivity* criterion, as it includes all contacts in the analysis and makes no previous assumptions about the importance of individual channels or channel order. In contrast with existing practical applications, the analyses are completely data driven, and the mechanics of model building and ad factor calculation are fully disclosed and reproducible.

Predictive accuracy measures how many conversion events get classified correctly. We use the 10-fold cross-validation, which is superior to leave-one-out validation or bootstrapping, since all the data serve as the holdout once (Kohavi, 1995; Sood, James, & Tellis, 2009). To ensure practical applicability, we measured predictive performance both within and out of sample. In Table 6, we report percentage correctly classified and compare our approach to the last click wins and first click wins heuristics. However, the discriminative power of this measure is limited in our context, where journey conversion rates do not exceed 2%. Standard metrics for classification accuracy, such as percentage correctly classified or log-likelihood, are poor metrics for measuring classification performance in the case of unequal misclassification costs or when class distribution is skewed (He & Garcia, 2009; Provost, Fawcett, & Kohavi, 1998). Besides percentage correctly classified, we therefore use a second measure to evaluate predictive accuracy. We choose the receiver operating characteristic (ROC) curve that decouples classification performance from class distributions and misclassification costs. A ROC curve is a two-dimensional graph; the true positive rate α is plotted on the x-axis, while the false positive rate $1 - \beta$ appears on the y-axis (Bradley, 1997; Fawcett, 2006). To compare our models, we reduce ROC performance to a single scalar value, the area under the ROC curve (AUC), which we calculate as follows (Bradley, 1997):

$$AUC = \sum_{i} \left\{ (1 - \beta_i * \Delta\alpha) + \frac{1}{2} \left[\Delta(1-\beta) * \Delta\alpha \right] \right\}, \qquad (4)$$

where

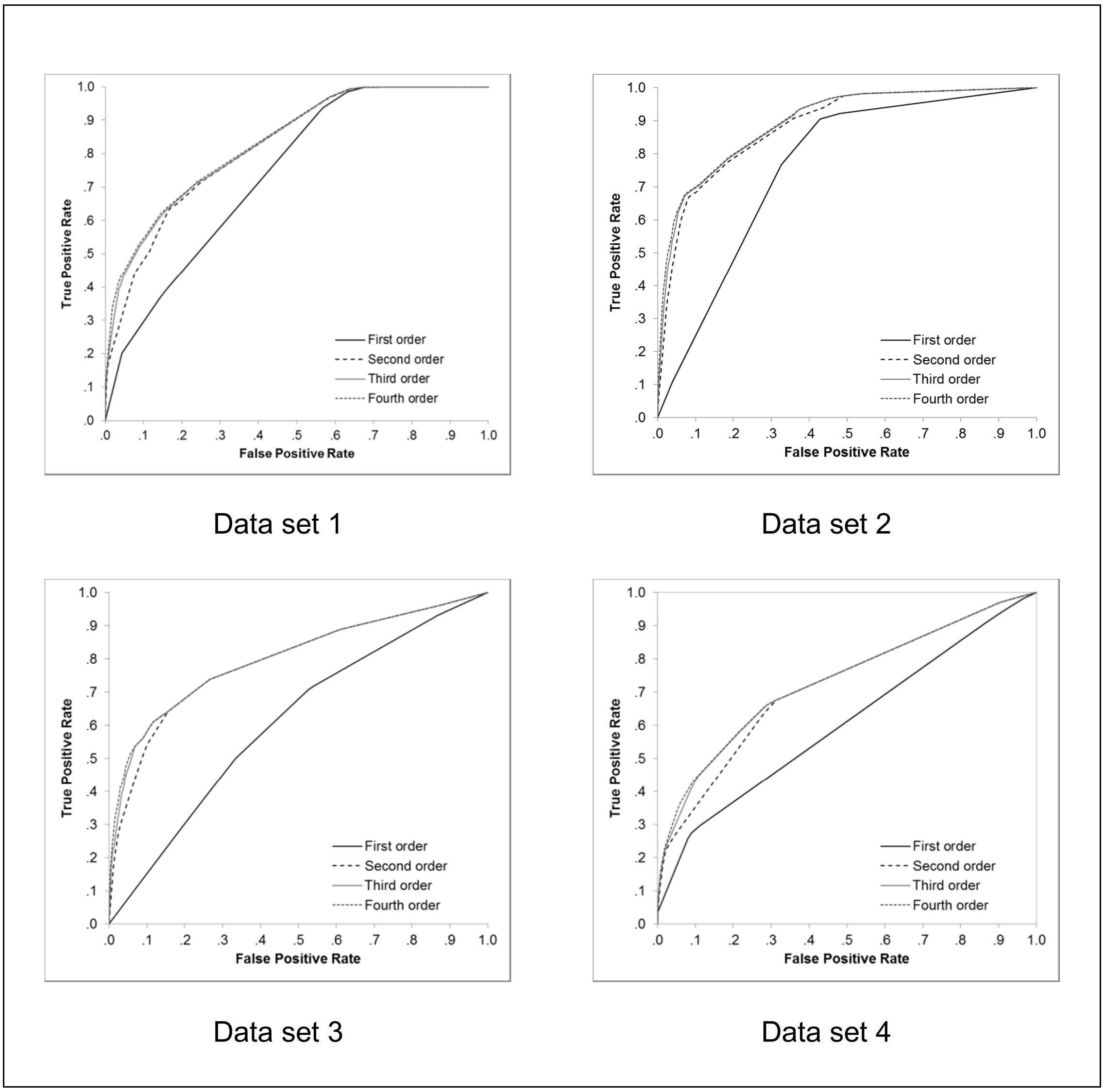
$$\Delta(1-\beta) = (1-\beta_i)\,(1-\beta_{i-1}), \qquad (5)$$

$$\Delta\alpha = \alpha_i - \alpha_{i-1}. \qquad (6)$$

The AUC measure can take values between 0 and 1, though a realistic classifier always shows an AUC of more than .5, the value reached by random guessing. Figure 4 contains the ROC curves for all models based on a within-sample evaluation of all journeys. In addition, we present detailed evaluation results and comparisons to existing heuristics in Table 6.

Figure 4

ROC Curves (Within Sample)—Study 2



Data set 1

Data set 2

Data set 3

Data set 4

Table 6

Predictive Accuracy—Study 2

			Model					
Measure	Sample	Data set	Base model	Second order	Third order	Fourth order	Last click wins	First click wins
Percentage correctly classified	Within sample	DS 1	.9836 (.0006)	.9836 (.0006)	.9836 (.0005)	.9841 (.0005)	.9836 (.0006)	.9836 (.0006)
		DS 2	.9915 (.0001)	.9915 (.0001)	.9915 (.0001)	.9915 (.0001)	.9915 (.0001)	.9915 (.0001)
		DS 3	.9812 (.0003)	.9812 (.0003)	.9812 (.0003)	.9814 (.0002)	.9812 (.0003)	.9812 (.0003)
		DS 4	.9800 (.0005)	.9800 (.0005)	.9801 (.0005)	.9802 (.0006)	.9800 (.0005)	.9800 (.0005)
	Out-of-sample	DS 1	.9836 (.0002)	.9836 (.0002)	.9838 (.0002)	.9840 (.0004)	.9836 (.0006)	.9836 (.0006)
		DS 2	.9914 (.0002)	.9914 (.0002)	.9914 (.0002)	.9914 (.0002)	.9914 (.0002)	.9914 (.0002)
		DS 3	.9812 (.0002)	.9812 (.0002)	.9812 (.0002)	.9814 (.0003)	.9812 (.0004)	.9812 (.0004)
		DS 4	.9800 (.0002)	.9800 (.0002)	.9800 (.0003)	.9801 (.0003)	.9800 (.0006)	.9800 (.0006)
AUC	Within sample	DS 1	.7408 (.0035)	.8208 (.0018)	.8314 (.0027)	.8336 (.0046)	.7400 (.0043)	.7144 (.0037)
		DS 2	.7593 (.0038)	.8834 (.0037)	.8930 (.0029)	.8958 (.0028)	.7617 (.0033)	.7733 (.0042)
		DS 3	.6079 (.0074)	.7941 (.0046)	.8024 (.0048)	.8035 (.0037)	.6087 (.0077)	.5994 (.0029)
		DS 4	.6012 (.0047)	.7187 (.0055)	.7293 (.0060)	.7278 (.0078)	.6028 (.0024)	.5528 (.0045)
	Out-of-sample	DS 1	.7388 (.0029)	.8214 (.0022)	.8313 (.0032)	.8326 (.0060)	.7407 (.0043)	.7138 (.0054)
		DS 2	.7597 (.0045)	.8832 (.0040)	.8926 (.0033)	.8943 (.0048)	.7618 (.0056)	.7728 (.0071)
		DS 3	.6078 (.0030)	.7909 (.0071)	.7982 (.0068)	.7994 (.0076)	.6092 (.0082)	.5989 (.0064)
		DS 4	.6048 (.0076)	.7178 (.0067)	.7296 (.0058)	.7285 (.0071)	.6046 (.0080)	.5550 (.0063)

Note. Standard deviations are in parentheses.

Although the overall predictive accuracy varies substantially between data sets, the relative predictive performance of the different model types is comparable, leading to similar rankings of the model types. Within and out-of-sample performance for our models is nearly identical, indicating a low risk of overfitting.[11] With the exception of data set 2, the base model outperforms the first click wins heuristics and leads to similar results as the last click wins approach. Increasing the memory capacity substantially improves the predictive performance of our graph-based models. The largest performance increase results from moving from the base model to second-order models. Increasing the memory capacity to three and four lags further improves predictive performance, though only marginally in most cases.[12]

The third evaluation criterion, *robustness*, applies to two measures. First, predictive accuracy should be robust across all cross-validation repetitions. Table 6 lists the standard deviations of the predictive performance measures for each model as well as for the two heuristics we use as a comparison. The results imply low overall variation. Second—and even more important, the variable used for attribution modeling should provide stable attribution results that offer a reliable basis for managerial decisions, such as budget shifts. Therefore, we specifically test the robustness of the *Removal Effect*(s_i) ad factor. For each model state s_i, we compute the average standard deviation of *Removal Effect*(s_i) across ten cross-validation repetitions. We report the stability of the removal effects as percentages of the average removal effect across all states, as the number of states per model and correspondingly the mean *Removal Effect*(s_i) varies. We summarize these validation results in Table 7. For all data sets in our sample, the average standard deviation as a percentage of the average removal effect increases with model order. As the increase in predictive performance when moving from third- to fourth-order models is marginal, second- and third-order models seem to offer a good trade-off between predictive accuracy and robustness.

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[11] This also holds true if we analyze subsets of our data sets including only longer journeys (journey length ≥ 5), whereas the out-of-sample performance for the first click wins and last click wins heuristics decreases significantly for these data sets.

[12] For subsets including only longer journeys (journey length ≥ 5), the increase in predictive performance when moving from the base model to higher-order models is less strong, yet higher-order models still outperform the first-order graph. Thus, our general findings regarding model order do not depend on the specific journey lengths in our sample.

Table 7

Removal Effect: Average Standard Deviation as % of Average Removal Effect (10-Fold Cross-Validation)—Study 2

	Model			
Data set	Base model	Second order	Third order	Fourth order
Data set 1	1.14%	1.92%	3.25%	5.43%
Data set 2	1.51%	2.10%	3.81%	7.57%
Data set 3	1.31%	1.72%	2.78%	5.15%
Data set 4	1.34%	1.80%	2.97%	4.67%

Although objectivity, predictive accuracy, and robustness represent necessary conditions for attribution models, additional criteria such as *interpretability* must be fulfilled to foster acceptance and application in practice. Even without advanced statistical knowledge, managers prefer to comprehend how models work and generate results (Lilien, 2011; Little, 1970; Lodish, 2001). The graphical representation (see Figure 2 and Figure 3) of our framework can help marketing executives understand the basic concept. In discussions with online marketing managers, we discovered that despite their initial skepticism toward algorithmic attribution approaches in general, the proposed framework was regarded as easy to interpret and well accepted. The output metrics can be provided in the same format as existing heuristics and are intuitively interpretable and easy to communicate to other stakeholders.

Because it requires no preliminary assumptions about channels or decision processes, our framework is highly *versatile*. The only prerequisite for building the graphical models we propose is the availability of historical, individual-level tracking data. Our framework can evaluate various conversion types, including sales, sign-ups, or leads, and easily integrate new online marketing channels. Analyses might run on different aggregation levels, such that users can analyze not only channels but also advertising campaigns or even different creatives.

Considering the large data volumes in online marketing (Bucklin & Sismeiro, 2009) and practitioners' requests for regular updates (Econsultancy, 2012a), *algorithmic efficiency* has become a decisive criterion for attribution models. Removal effects can be calculated efficiently in $O(|S|^2)$ time (Cormen, Leiserson, Rivest, & Stein, 2009) and hence allow for frequent model updates. However, as the number of states increases exponentially with the order of the Markov chain, we limit our analyses to lower-order models in order to allow for updates in near real-time.

Combining objectivity and measures of model fit with practical considerations, we recommend using second- or third-order models for standard attribution analyses. Using higher-order models also yields additional insights into channel interactions, further increasing managers' understanding of the interplay across channels. We illustrate these findings with exemplary analyses next.

3.5.2 Attribution Results

We compare the attribution results of our proposed framework with the last and first click wins heuristics, that is, the attribution approaches most widely used in industry practice (Econsultancy, 2012a). Given our evaluation results, we use third-order Markov models in our comparison. Our analyses are based on a 10-fold cross-validation and show the average contribution of each channel towards final conversions. We present the results in Table 8.

Table 8
Attribution Results Compared to Existing Heuristics (in %)—Study 2

	Data set 1			Data set 2			Data set 3			Data set 4		
	Markov graph (Third order)	Last click wins	First click wins	Markov graph (Third order)	Last click wins	First click wins	Markov graph (Third order)	Last click wins	First click wins	Markov graph (Third order)	Last click wins	First click wins
Type In	n/a	n/a	n/a	35.34%	43.91%	40.28%	27.75%	29.77%	25.51%	18.84%	22.02%	13.71%
SEA	46.13%	53.19%	56.36%	19.86%	22.27%	23.60%	18.37%	20.16%	20.70%	59.59%	60.98%	76.26%
SEO	19.38%	16.76%	16.67%	15.82%	13.66%	13.24%	21.97%	21.33%	21.12%	9.37%	7.79%	5.30%
Affiliate	19.92%	20.17%	13.66%	8.65%	7.83%	6.87%	n/a	n/a	n/a	4.72%	3.67%	0.42%
Price Comparison	5.35%	4.78%	6.05%	0.20%	0.11%	0.12%	n/a	n/a	n/a	3.51%	2.17%	2.21%
Newsletter	4.60%	2.93%	4.28%	14.56%	8.76%	11.94%	1.23%	1.15%	1.32%	n/a	n/a	n/a
Referrer	n/a	n/a	n/a	2.01%	1.67%	2.58%	5.67%	6.85%	7.52%	1.87%	1.65%	1.96%
Retargeting	1.22%	0.67%	0.78%	n/a	n/a	n/a	0.05%	0.01%	0.00%	2.10%	1.72%	0.16%
Display	0.90%	0.14%	0.21%	3.56%	1.79%	1.37%	n/a	n/a	n/a	n/a	n/a	n/a
Social Media	n/a	n/a	n/a	n/a	n/a	n/a	24.96%	20.73%	23.83%	n/a	n/a	n/a
Other	2.50%	1.36%	1.97%	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
χ2		12,908	18,239		39,676	28,435		5,998	5,076		3,681	38,683
df		7	7		7	7		6	6		6	6
p		<.001	<.001		<.001	<.001		<.001	<.001		<.001	<.001

Note. Values are averages from 10-fold cross-validation. χ2 values in comparison to Markov graph attribution results.

We observe significant differences for the results of the Markov model and those of the last and first click wins heuristics. The channels SEO, display, and retargeting are consistently undervalued by the heuristic attribution approaches, whereas the contribution of SEA seems to be overestimated. Direct type-ins, when users directly access the company website, seem to be overvalued by the last click wins approach but undervalued by first click wins, though not in all cases. The remaining channels leave a more ambiguous picture, such that the implications need to be derived and verified individually for each data set.

In addition, higher-order models offer a more detailed view, which we illustrate using the second-order model for data set 1 in Table 9. For many channels, including SEA and newsletter, the increase in overall purchase probability is highest right after the START state, near the beginning of the journey—which corresponds with the high share of one-click journeys in the data set. Sequences of identical channels show high removal effects, which might indicate channel preferences for some users. For example, affiliate preceded by affiliate has a percentage removal effect of 5.31%, whereas the average removal effect for affiliate preceded by another channel is only 1.22%. Although SEO and affiliate are comparable in their total effects, the removal effect of SEA preceded by affiliate is significantly lower than that of SEA preceded by SEO. Furthermore, SEO seems to work especially well if preceded by another interaction in a search context (SEO or SEA). In addition to increasing predictive performance, the application of models with higher model orders thus enables advertisers to gain a more detailed understanding of the interplay across channels.

Table 9

Attribution Results for Second Order Model (Data Set 1)—Study 2

	Preceding channel								
Current channel	START	Affiliate	Display	News-letter	Price com-parison	Retar-geting	SEA	SEO	Un-defined
Affiliate	8.10%	5.31%	0.15%	0.20%	0.23%	0.08%	2.61%	1.00%	0.15%
Display	0.62%	0.03%	0.42%	0.02%	0.02%	0.01%	0.09%	0.02%	0.01%
Newsletter	1.91%	0.07%	0.04%	0.99%	0.02%	0.02%	0.27%	0.13%	0.01%
Price comparison	3.07%	0.04%	0.03%	0.04%	1.36%	0.01%	0.22%	0.05%	0.04%
Retargeting	0.34%	0.04%	0.02%	0.02%	0.03%	0.24%	0.20%	0.06%	0.01%
SEA	32.52%	0.84%	0.35%	0.48%	0.34%	0.15%	14.27%	2.43%	0.47%
SEO	7.78%	0.42%	0.07%	0.10%	0.11%	0.06%	4.40%	4.75%	0.08%
Other	1.12%	0.03%	0.02%	0.02%	0.01%	0.01%	0.27%	0.06%	0.50%

3.6 Discussion

3.6.1 Theoretical Implications

Our framework contributes to marketing theory in several ways. First, we propose a novel, graph-based framework for analyzing multichannel online customer journeys, represented as Markov walks in directed graphs. In addition to our base model, we further introduce higher-order Markov graphs, in which the present depends on the last k observations. The representation in directed Markov graphs supports the calculation of the *Removal Effect(s_i)* ad factor, defined as the change in probability of reaching the *CONVERSION* state from the *START* state when s_i is removed from the graph. We use the removal effect to derive state and channel contributions, respectively. In total, we rigorously evaluate four model alternatives according to our criteria using four, large-scale, real-life data sets. A comparison of the results against existing attribution heuristics shows substantial differences between the results of the Markov graphs and the last and first click wins approaches. Thus we provide an alternative to widely used, often misleading attribution heuristics applied in practice. We also extend existing attribution literature (Abhishek et al., 2012; Berman, 2013; Dalessandro et al., 2012; Haan et al., 2013; Kireyev et al., 2013; Li & Kannan, 2014; Shao & Li, 2011; Xu et al., 2014), by introducing an approach that meets both academic standards of objectivity, predictive accuracy, and robustness and additional criteria relevant for implementation in practice.

Second, our evaluation results offer new insights into online marketing effectiveness in a multichannel setting. The higher-order models significantly outperform first-order models regarding predictive accuracy, which indicates that channels in customer journeys should not be analyzed in isolation. Similarly, prior findings show that browsing patterns within a website are not first-order Markovian and can be predicted better by higher-order Markov models (Chierichetti et al., 2012; Montgomery et al., 2004). Thus our results add to the evidence that last click wins attribution heuristics cannot capture the full contribution of online channels. In line with other studies (Abhishek et al., 2012; Li & Kannan, 2014; Xu et al., 2014), we assert that some channels, such as display, are undervalued by existing attribution heuristics, whereas the contributions of other channels, such as SEA, may be overestimated. Using four, large-scale data sets in three different industries, we affirm some results in previous studies that used only a single industry and were based on significantly smaller data sets. However, the variation in our results (e.g., for price comparison, newsletter, or the general importance of channels) shows that insights pertaining to online channel effectiveness and attribution should not be generalized from findings based on a single data set; they need to be analyzed on a case-by-case basis. This outcome reemphasizes the need for an easily applicable, versatile attribution framework.

Third, we develop a comprehensive set of six criteria required for successful attribution models. Building on existing literature related to the acceptance of marketing decision models in practice (Leeflang & Wittink, 2000; Lehmann et al., 2011; Lilien, 2011; Little, 1970, 1979, 2004; Lodish, 2001), we ensure scientific rigor by assessing objectivity, predictive accuracy, and robustness; we also include criteria to encourage application in practice, namely, interpretability, versatility, and algorithmic efficiency. Whereas previous studies have discussed selected properties for attribution methods (Dalessandro et al., 2012; Shao & Li, 2011), we present the first exhaustive set of criteria that acknowledges practitioners' requirements. Clear criteria reduce the barriers to applying attribution techniques in managerial practice (Econsultancy, 2012a) and foster standardization and cross-industry acceptance (Dalessandro et al., 2012). Increased objectivity in evaluating the contribution of online marketing channels also should result in fairer remuneration for advertising-financed publishers (Jordan et al., 2011). The incentives of advertisers and other market actors, such as publishers or agencies, are seldom congruent (Abou Nabout, Skiera, Stepanchuk, & Gerstmeier, 2012; Berman, 2013), which creates a demand for independent, objective criteria to assess attribution models.

Finally, our research answers a call for marketing impact models based on individual-level, single-source data, which help identify optimal levels of marketing expenditures for each channel (Rust, Ambler, Carpenter, Kumar, & Srivastava, 2004). Methodologically, we provide a new perspective on path data in marketing (Hui et al., 2009) and present efficient methods for handling large, real-world advertising data sets (Bucklin & Sismeiro, 2009).

3.6.2 Managerial Implications

We implemented our attribution framework in a real industry environment, such that we can illustrate how our approach contributes to marketing practice. We developed a prototype of our framework, including all four model types and implemented it as a real-life system at intelliAd Media GmbH, a subsidiary of Deutsche Post AG. IntelliAd integrated the attribution tool in its multichannel tracking solution. Thus far, several test clients, operating in the fashion, sports equipment, and telecommunications industry, have applied our attribution tool in practice, confirming its high usability and positive impact on marketing effectiveness; however, we cannot disclose explicit test results for confidentiality reasons.

Scientifically validated attribution models help resolve several managerial problems. Decision making is a complex task for online advertisers, in that it spans various online marketing channels and goals (Raman et al., 2012). Our framework can facilitate independent managerial (budget) decisions by providing easy-to-interpret, objective information that factors out subjective influences. Budgets should be allocated across channels according to their value contribution. Certain channels may be underrepresented; others contribute little to the company’s success at relatively high costs. Tucker (2012) finds that attribution can enable advertisers to substitute towards more successful campaigns, leading to more conversions at lower costs.

Furthermore, to shape digital marketing strategies, advertisers need to step into the shoes of customers to understand and anticipate their online behavior. In other words, advertisers need to know where to meet customers online to make strategic channel decisions. Our framework reveals which channels customers use and to what degree they drive marketing effectiveness. Thus advertisers can use it to constantly review and adjust their strategic online channel deployment. Such usage also should enhance decision makers’ expertise and update their mental models, which are prone to systematic errors and biases (Tversky & Kahneman, 1974). Online marketing managers often base their decisions on simple heuristics, combined with personal expertise. Daily work with our model and its results would help them gradually build new knowledge and better understand the interplay of online marketing measures with their success drivers. Even when detailed tracking data are available, personal preferences are likely to affect budget and channel decisions. By setting our model in the context of well-known approaches such as last click wins heuristics, we give decision makers a means to calibrate their marketing measures, anticipate their impact, and sharpen their expertise, such that they can improve their future marketing decisions.

The introduction of data-driven attribution also suggests effects on hierarchical structures within organizations and group decision making. Budget decisions are often group decisions, resulting from multiple meetings that are influenced by hierarchical superiority or other influences, such as individual agendas or company politics (Fischer, Albers, Wagner, & Frie, 2011; Sinha & Zoltners, 2001). In meeting the objectivity criterion, our approach is devoid of personal assumptions, preferences, and other biases that could adversely affect the decision process (Bruggen, Smidts, & Wierenga, 1998; Leeflang & Wittink, 2000)—in marked contrast with existing, widely used attribution methodologies that rely on the (pre)definition of channel or position weights by advertisers (Econsultancy, 2012a; The CMO Club & Visual IQ, Inc., 2014). As a result, team-based budget decisions can be made in discussion leveraging both practitioners' experience and unbiased data-driven analyses.

Moreover, the versatility of our framework makes it generalizable to many industries and applications, unlike other attribution techniques, whose highly sophisticated solutions cannot be transferred easily to other firms or contexts (Abhishek et al., 2012; Haan et al., 2013; Kireyev et al., 2013; Li & Kannan, 2014). Regarding its output, our model flexibly and efficiently evaluates various conversion types (e.g., sales, sign-ups, leads), depending on the advertiser's specific aim. In this sense, our model sheds light onto multiple functions across the company's value chain, not just sales. For example, recruiters need to understand where to meet qualified candidates online, where they lose them, and how to develop appropriate measures to attract them.

Compared with other attribution models that are purely retrospective, our proposed graph-based framework can also be used prospectively. Thus a possible application is real-time bidding in ad exchanges, where advertisers can bid on advertising slots for specific users using information such as the user's location or previous surfing behavior (Muthukrishnan, 2009). Advertising exchanges serve as intermediaries between online publishers and advertisers. When a user visits a webpage with an open display advertising slot, the publisher posts the slot in the exchange. Relying on information provided about the user, such as his or her browsing history, advertisers can bid on the slots. After the auction, the publisher serves the winning advertiser's creative to the user. This entire process happens in milliseconds, between the time the user requests a page and the time the page is rendered on the screen (Muthukrishnan, 2009). Using our framework, advertisers can more accurately calculate the conversion probability *Eventual Conversion*(s_i) of a customer, given his or her previous customer journey. The predicted change in *Eventual Conversion*(s_i) when the advertiser wins the auction and the advertisement is shown to the user also can be used to calculate the value of this slot on an individual user level and thus determine a maximum cost-effective bid. The short timeframe for determining a bid means that the primary system-related restriction for real-time bidding is algorithmic efficiency. Once the model we propose has been fully built though, the calculation of ad factors such as *Eventual Conversion*(s_i) diminishes to a single matrix look-up, which makes the framework highly attractive for real-time applications in ad exchanges.

3.7 Outlook

Our research has several limitations that may stimulate research on attribution and online marketing effectiveness. Although we used four data sets from different industries, some findings may be company specific. The customer journeys in these data sets were short on average, including a high number of one-click journeys. However, sophisticated attribution is not required for journeys consisting of just a single click: In that case, both the "last click wins" and the "first click wins" heuristics deliver objective results that would satisfy our criteria, whereas longer journeys increase advertisers' need to understand channel contributions. We therefore recommend applying this framework to other industries and including not just clicks but views as well. The high versatility of our approach would also allow to integrate offline marketing channels, if exposure data are available on an individual level.

We did not include the varying costs of different online advertising channels and potential differences in conversion revenues in the analysis. To evaluate the effectiveness of online marketing channels, companies should consider costs incurred per channel, profits from conversions, and—potentially in a second step—the CLV of customers acquired. As Chan, Wu, and Xie (2011) show, customers acquired through different online marketing channels differ in CLV. Our graph-based approach is well suited for such extensions with additional data, thus further research should include this information to advance attribution.

The attribution problem is by definition endogenic; it measures the relative effectiveness of channels in a given setting (Li & Kannan, 2014), so the results are conditional on a number of management decisions, such as channels used, budget limits per channel, or ad creatives employed. We thus cannot directly derive general recommendations for an optimal budget allocation. Nevertheless, objective attribution is a necessary prerequisite for managers to optimize their budget decisions: if the budget share of a channel is higher than its actual contribution as measured by our attribution framework, advertisers should review their budget allocations. Subject to the availability of longitudinal data, attribution results calculated using our framework could also serve as a basis for developing optimization algorithms.

Finally, a strict causal interpretation of customer journeys is difficult, because alternative explanations may exist for the correlations between conversions and advertising exposures. Some channels, such as retargeting, explicitly try to target customers who have a higher propensity to purchase (Lambrecht & Tucker, 2013). Even without special targeting, observed correlations might be due to selection effects, such as an activity bias (Lewis, Rao, & Reiley, 2011). Driven by the managerial problem of attributing credit to channels on an aggregated level and the sparsity of individual-level customer journey data, we also do not address consumer heterogeneity (Allenby & Rossi, 1999). To establish a strict causal relationship between advertising and individual purchase behavior, large-scale field experiments with randomized exposure are required. Such experiments are hard to implement in practice, especially in multichannel settings, but comparing our attribution modeling framework against experimental results would be a valuable follow-up.

We thus urge marketing researchers to continue to analyze online advertising effectiveness in multichannel settings to make sense of the newly available wealth of data gained from new tracking technologies. We believe this work contributes to ongoing efforts to bridge the gap between academic research and managerial practice and to establish rigorous, practically applicable models for measuring marketing effectiveness.

4 Analyzing Multichannel Online Customer Journeys for an Online Retailer: A Categorization Approach

Eva Anderl[13]

Retailers can choose from a plethora of channels to reach consumers on the Internet, such that potential customers often use a number of channels along the customer journey. Due to increasing complexity and sparse data the author proposes a categorization approach to investigate how channel usage along the customer journey facilitates inferences on underlying purchase decision processes. The approach is tested on two large clickstream data sets using a proportional hazard model with time-varying covariates. By categorizing channels along the dimensions of contact origin and branded versus generic usage, the author finds meaningful interaction effects between contacts across channel types, corresponding to the theory of choice sets. Including interactions based on the proposed categorization significantly improves model fit and outperforms alternative specifications. The results will help retailers gain a better understanding of customers' decision-making progress in an online multichannel environment and help them develop individualized targeting approaches for real-time bidding.

4.1 Introduction

When trying to reach potential customers on the Internet, online retailers can choose from a variety of channels, including search engine marketing, display marketing, as well as email and social media (Raman et al., 2012). Throughout this paper, we use the term "online channels" to describe the online marketing instruments that retailers use to reach potential customers on the Internet. Because an increasing number of firms are utilizing multiple marketing channels simultaneously (Turn Inc., 2013), potential customers can interact with said firms using a number of different channels along their online customer journey. An online customer's journey (Lee, 2010) or path to purchase (Haan et al., 2013; Xu et al., 2014) includes all contacts of an individual customer with an online retailer over all online channels preceding a potential purchase decision. Recent technological advances allow retailers to track

[13] The author thanks Jan Schumann and Werner Kunz for their insightful comments on this manuscript.

these journeys on an individual level, providing data for a much deeper analysis of individual purchase decision processes than was previously possible. Analyzing these journeys offers new opportunities to predict individual customers' purchase propensities and to develop individualized marketing strategies.

Academic research on online marketing in a multichannel environment has only recently gained momentum—potentially due to increasing data availability. Previously, online marketing research primarily investigated the effectiveness of single channels such as display and search in isolation. Most of the recent studies on multichannel online marketing focus on the interplay of selected channels, especially display and search (Abhishek et al., 2012; Kireyev et al., 2013; Lewis & Nguyen, 2014; Nottorf, 2014; Papadimitriou et al., 2011; Xu et al., 2014). However, in today's business world, the actual number of online channels used is significantly higher. For instance, European marketers report using seven channels in parallel (Teradata Corporation, 2013). Outside of a few recent exceptions (Anderl et al., 2014; Klapdor, 2013; Li & Kannan, 2014), there is scant research covering the full spectrum of online channels available to online retailers.

The plethora of online channels increases the complexity of analyses on an individual user level, namely because data points become sparse with rising dimensionality. To investigate whether and how channel usage along the customer journey permits inferences on the underlying purchase decision process despite this "curse of dimensionality" (Bellman, 1961), we propose categorizing online channels along the dimensions of contact origin and branded versus generic usage. Using a large, individual-level data set from an online fashion retailer, we test our approach using a proportional hazard model with time-varying covariates and compare it to alternative model specifications. To ensure generalizability, we additionally conduct a robustness check using a second data set. By categorizing channels, we find meaningful interaction effects between contacts across channel types that allow inferences to be made regarding customers' purchase decision processes.

The contribution of our study is at least fivefold: First, we find support for the theory of choice sets (Hauser & Wernerfelt, 1990; Shocker et al., 1991; Spiggle & Sewall, 1987) in an online retail context and thus answer the call for a reinvestigation of existing marketing theory in the Internet environment (Yadav & Pavlou, 2014). Second, we develop and test a new approach for investigating the interplay of online channels along the customer journey in spite of sparse multidimensional data. The categorization we propose outperforms alternative approaches (Haan et al., 2013; Klapdor, 2013) and allows one to identify meaningful interaction effects between contacts across channel types. Third, the existence of significant interaction effects along the customer journey further substantiates the idea that analyzing channels in isolation may lead to erroneous conclusions on channel effectiveness and suboptimal managerial decisions (Li & Kannan, 2014; Xu et al., 2014). Fourth, our approach helps to close the gap between online marketing research and practice (Yadav & Pavlou, 2014) by covering the full spectrum of online channels available to marketers. Whereas existing research on multichannel online marketing mainly focuses on the interplay of selected channels, we include eight different channels in our analysis and thereby offer a realistic picture of channel diversity. Finally, our results can help retailers develop individualized targeting strategies based on contact histories. This can be used in real-time bidding in ad exchanges, where marketers can bid on advertising slots for specific users based on information such as the user's location or previous surfing behavior (Muthukrishnan, 2009). According to a recent survey among online marketing managers, 85% of advertisers already apply such programmatic buying strategies (Winterberry Group, 2013) and usage is expected to grow rapidly in the coming years (eMarketer, 2013a). Our results also allow online retailers to optimize the landing pages that users reach when clicking on an ad in order to accommodate different information needs.

The remainder of this article proceeds as follows: We begin by introducing the range of online channels available to retailers and summarize the existing research on multichannel online marketing. Building on prior research on purchase decision processes, we then develop our categorization approach for analyzing the interplay of channels along the customer journey. After briefly presenting alternative categorization approaches, we provide details on the real-life data set used to evaluate our model. We elaborate on said model in the following section, test it against alternative approaches, and discuss estimation results. Afterward, in order to assess the robustness of our results, we conduct a similar analysis using data from a different industry. We continue with an overview of our findings and shed light on implications before concluding the paper with a discussion of limitations and avenues for future research.

4.2 Background

4.2.1 Online Marketing Channels

To illustrate the growing diversity of channels available to online retailers and to provide definitional clarity, we start with a brief overview of frequently used online channels.

Type-In. First of all, customers can directly access an online retailer's website by entering the URL in the address box of the browser or by locating a bookmark, favorite, or shortcut. Following discussions with practitioners, we explicitly include these direct "type-ins" as a channel. From a consumer perspective, the boundaries between search and type-ins have become increasingly fluid (Lee & Sanderson, 2010), such that excluding type-ins from the analysis would distort our results.

Search. A consumer searching for a keyword in a general search engine (e.g., Google, Bing, Yahoo!, Baidu) receives two types of results: organic search results selected and ranked by a search algorithm, and sponsored search results, also known as paid search or search engine advertising (SEA; Abou Nabout, Lilienthal, & Skiera, 2014; Ghose & Yang, 2009). Organic search results (also called search engine optimization; SEO) are free of charge, yet many firms invest time and money into optimizing their position on the results page (Dou, Lim, Su, Zhou, & Cui, 2010). SEA is sold via continuous, generalized, second-price, sealed-bid auctions; however, retailers only pay for users who actually click on their ads (Abou Nabout et al., 2014).

Price Comparison. Price comparison or comparison-shopping agents are Internet service platforms that allow users to compare prices and product information (Iyer & Padmanabhan, 2006). In general, firms pay to be listed on the search results page, which provides direct links to the sales page of the selected product (Breuer et al., 2011).

Display. In display advertising, also known as banner advertising, digital graphics are embedded in Web content pages. When users click on the display advertisement, they are redirected to the advertiser's website (Hollis, 2005). While click-through rates have declined continuously and are now below 0.1% (Fulgoni & Mörn, 2009), unclicked display ads may have a positive effect on brand equity measures such as brand awareness and advertising recall (Drèze & Hussherr, 2003).

Retargeting. Retargeting is a special form of display advertising that uses a consumer's browsing history to deliver personalized display banners (Lambrecht & Tucker, 2013). In the case of generic retargeting, retailers specifically target Internet users who have previously visited their website with generic ads. Dynamic retargeting ads display the exact product or product category that the consumer has looked at before (Lambrecht & Tucker, 2013).

Affiliate. In affiliate advertising, which is also known as referral marketing or lead generation, firms place links for their business on partner websites. The partner website earns a commission whenever a visitor follows the link and finalizes a predefined transaction, such as a purchase or a newsletter registration (Libai, Biyalogorsky, & Gerstner, 2003; Papatla & Bhatnagar, 2002).

Email. Email advertising includes both ads within an email and entirely promotional emails (PriceWaterhouseCoopers, 2014). Promotional newsletters require the consumer's permission (Tezinde, Smith, & Murphy, 2002), which distinguishes email advertising from unsolicited commercial email messages, also referred to as spam (Morimoto & Chang, 2006).

Other channels, which we do not cover in detail in this study, include video (Luo, Jiang, & Yi, 2012), social media marketing (Kumar, Bhaskaran et al., 2013), mobile advertising (Goh, Chu, & Soh, 2009), classifieds (Evans, 2009), and sponsorship and product placements, for example in blogs (Zhu & Tan, 2007). Emerging channels, such as online in-game advertising (Terlutter & Capella, 2013) or in-app advertising (Juniper Research, 2014), complement the evolving spectrum of online marketing channels.

4.2.2 Multichannel Online Marketing

Existing research on multichannel marketing in the offline world takes two general forms: one is based on laboratory research using selected channels and the other involves analyzing data on an aggregated level, such as spendings per channel. This bifurcated research focus is probably due to limited data availability, because measuring individual-level exposures to multiple offline channels is highly challenging (Danaher & Dagger, 2013). Research on online marketing effectiveness has long been focused on single exposures and—more recently—interaction effects within channels. Chatterjee et al. (2003) analyze click probabilities both within and between sessions and are the first to draw attention to interaction effects in display advertising. Within-channel interaction effects exist both in display (Braun & Moe, 2013; Manchanda, Dubé, Goh, & Chintagunta, 2006) and search (Rutz & Bucklin, 2011).

Multichannel online marketing effectiveness has only recently gained the attention of marketing researchers. Most studies focus on two or three selected channels, often investigating the relationship between other channels and search. For example, research indicates that display (Lewis & Nguyen, 2014; Papadimitriou et al., 2011) as well as TV (Joo, Wilbur, Cowgill, & Zhu, 2014) advertisements influence the number of relevant search queries. Kireyev et al. (2013) and Nottorf (2014) confirm interaction effects between display and SEA. Xu et al. (2014) find that display advertisements stimulate subsequent visits through other advertisement formats such as paid search. These results are congruent with findings that display and search affect different stages of the purchase decision process (Abhishek et al., 2012). For other channels, the picture is less clear and thus calls for further investigation: For instance, Breuer et al. (2011), using aggregated data, do not find interaction effects between display, email, and price comparison advertising. In an experimental setting, Chang and Thorson (2004) find that synergy between TV and display leads to higher attention and message credibility. Relying on single-source data, Bollinger, Cohen, and Jiang (2013) report a positive interaction between TV and online display exposures in the creation of goodwill.

Very few studies cover the full spectrum of channels currently used by online marketers. Two recent studies compare the effectiveness of multiple online and offline marketing channels (Danaher & Dagger, 2013; Haan et al., 2013), yet do not analyze interaction effects between channels. Li and Kannan (2014) developed an online attribution model that includes six different online channels, estimating the carryover and spillover effects of prior contacts on visits and purchases. They find that paid and organic search reduce the costs of visiting through display and email. From a practice-oriented perspective, Anderl et al. (2014) present an attribution model based on Markov graphs to measure the contribution of multiple online channels.[14] Meanwhile, Klapdor (2013) shows how practitioners can use the number and the types of channels in a customer journey to predict conversions in online shops.

[14] See Study 2.

Table 10 provides an overview of existing research on multichannel online marketing, including information on the channels investigated, aggregation level and methods used, and the analysis of interaction effects. This summary illustrates that, despite increasing research interest, there is little knowledge on the interplay of a larger number of online channels.

Table 10

Research on Multichannel Online Marketing—Study 3

Study	Online/ Offline	Channels	Aggregation level	Approach	Method	Interactions between channels	Key results on multichannel marketing
Breuer et al. (2011)	Online only	Display, Email, Price Comparison	Aggregated (per day)	Field data	GLS regression	No	Short- and long-term effects of online marketing channels: length of effects is not always aligned with intensity
Papadimitriou et al. (2011)	Online only	Display, SEA	Individual	Field experiment	Confidence interval analysis	Yes	Display views increase the number of relevant search queries
Abhishek et al. (2012)	Online only	Display, SEA	Individual	Field data	HMM	No	Display and SEA affect different stages of the purchase decision process
Bollinger et al. (2013)	Online + Offline	Display, Social Media, TV	Individual	Field data	Multivariate logit (Bayesian)	Yes	Positive interactions between TV and online for goodwill; no interaction effects for consumer utility
Danaher and Dagger (2013)	Online + Offline	Catalog, Display, Magazine, Mail, Newspaper, Radio, Search, Social Media, TV	Individual	Field data (survey-based)	Type II Tobit	No	7 of 10 channels significantly influence purchase outcomes
Haan et al. (2013)	Online + Offline	Email, Portals, Price Comparison, Radio, Referrals, SEA, TV	Aggregated (per day)	Field data	SVAR model	No	Customer-initiated channels are more effective than firm-initiated channels
Kireyev et al. (2013)	Online only	Display, SEA	Aggregated (per week)	Field data	Persistence modeling	Yes	Display ads increase the number of SEA clicks and conversions
Klapdor (2013)	Online only	Affiliate, Display, Email, Referrals, SEA, SEO	Individual	Field data	Logistic regression	Yes	Consumers’ reactions to advertising messages through multiple channels are strong predictors of purchase propensity

Study	Online/ Offline	Channels	Aggregation level	Approach	Method	Interactions between channels	Key results on multichannel marketing
Anderl et al. (2014)	Online only	Affiliate, Display, Email, Price Comparison, Referrals, Retargeting, SEA, SEO, Social Media, Type-In	Individual	Field data	Markov graphs	No	Attribution model to capture the contribution of online advertising channels
Lewis and Nguyen (2014)	Online only	Display, Search	Individual	Quasi-experiment	OLS regression	Yes	Display views increase the number of relevant search queries (also for competitors)
Li and Kannan (2014)	Online only	Display, Email, Referrals, SEA, SEO, Type-In	Individual	Field data + Field experiment	Hierarchical Bayes model	Yes	Carryover and spillover effects between online marketing channels
Nottorf (2014)	Online only	Display, SEA	Individual	Field data	Binary logit (Bayesian)	Yes	Positive interaction effects between display and SEA influencing consumer click probabilities
Xu et al. (2014)	Online only	Display, SEA, Other	Individual	Field data	Mutually exciting point process model	Yes	Display ads stimulate visits through other channels
Our study	Online only	Affiliate, Display, Email, Partner Website, Price Comparison, Retargeting, SEA, SEO, Type-In	Individual	Field data	Proportional hazard model with time-varying covariates	Yes	Categorization of channels according to contact origin and branded versus generic usage allows to identify interaction effects over time

4.2.3 Purchase Decision Processes

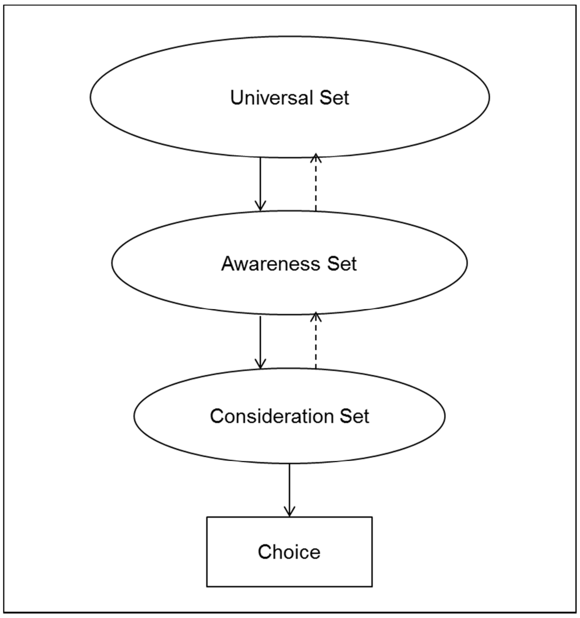
Although there is considerable dissent regarding exact definitions (Hauser & Wernerfelt, 1990), marketing research generally agrees on conceptualizing purchase decisions as multistage processes (Roberts & Lattin, 1997). The theory of choice sets (Hauser & Wernerfelt, 1990; Shocker et al., 1991; Spiggle & Sewall, 1987) has a long history in marketing and has been empirically validated in multiple studies (Roberts & Lattin, 1997; Yadav & Pavlou, 2014).[15] It thus lends itself as a promising foundation for analyzing online customer journeys. However, whereas multistage decision-making within online stores has been subject to extensive research (Häubl & Trifts, 2000; Moe, 2006; Wu & Rangaswamy, 2003), the application of choice set theory to multichannel online marketing research is surprisingly limited (Yadav & Pavlou, 2014). Instead, especially practitioners have put forward alternative conceptualizations of online consumer decision processes without relating them to existing marketing theory (e.g., Court, Elzinga, Mulder, & Vetvik, 2009; Edelman, 2010).

According to the theory of choice sets, customers are only aware of a limited number of alternative brands that satisfy their goals—the awareness set. A subset of the awareness set, the consideration set, is actively considered for a specific purchase. It is important to note that this consideration set is dynamic, since consumers can add or remove elements until they decide to make a final choice (Hauser & Wernerfelt, 1990; Shocker et al., 1991; Spiggle & Sewall, 1987). Figure 5 illustrates the nested structure of choice sets.

[15] For a review see Shocker, Ben-Akiva, Boccara, and Nedungadi (1991) and Roberts and Lattin (1997).

Figure 5

Theory of Choice Sets—Study 3



Note. Adapted from "Consideration set influences on consumer decision-making and choice: Issues, models, and suggestions," by A. D. Shocker, M. Ben-Akiva, B. Boccara, & P. Nedungadi, 1991, *Marketing Letters*, 2(3), p. 184.

It is not possible to impute choice sets with certainty based on observational data (Shocker et al., 1991). Nevertheless, consumers' informational needs change during the purchase decision process (Payne, Bettman, & Johnson, 1988), such that channel usage along the customer journey may allow inferences on the underlying decision process. A typical two-stage process may look as follows: After identifying a larger set of alternatives, the consumer seeks additional information to evaluate the most promising alternatives in more depth before making a purchase decision (Häubl & Trifts, 2000). In the following, we present an approach for categorizing online channels in order to infer progress or stagnation in the choice set formation process.

4.3 Categorization of Online Channels

The proliferation of online channels has created a need to categorize these marketing instruments in order to analyze interaction effects along the customer journey. The number of potential interactions grows exponentially with the number of channels used, but at the same time, data points become increasingly sparse—a phenomenon known as the curse of dimensionality (Bellman, 1961). To reduce the number of potential combinations and thereby allow for meaningful analyses of interaction effects along the customer journey, we propose categorizing online channels according to contact origin and branded versus generic usage.

4.3.1 Proposed Categorization Approach

Whereas marketing activities have traditionally been initiated or ”pushed” by the firm, marketing contacts in the online world are often initiated by customers ("pull"; Shankar & Malthouse, 2007). For example, potential customers trigger SEA by an active search, whereas in firm-initiated channels (FICs), such as display advertising, the advertiser determines timing and exposures. Customer-initiated channels (CICs) include search engine marketing (organic and paid), price comparison advertising, and direct type-ins. FICs encompass display advertising, retargeting, and emails, among others. Contact origin is an important differentiator for online marketing channels (Haan et al., 2013; Li & Kannan, 2014; Wiesel et al., 2011): Previous studies have shown that CICs have a higher sales elasticity than FICs, arguing that they are less intrusive and more relevant (Haan et al., 2013; Wiesel et al., 2011). In their study on online marketing attribution, Li and Kannan (2014) find spillover effects of CICs in reducing the costs of visiting through FICs.

We aim to further differentiate CICs according to branded versus generic usage in order to allow inferences on the underlying purchase decision process. In selected CICs, such as type-ins and searches for branded keywords (“branded search”), customers actively use the brand name while initiating the contact. Other CICs (e.g., price comparison websites) are used in a generic way. The differentiation between branded and nonbranded (i.e., generic) keywords is well known in research on SEA, yet we do not know of applications outside this research area. Research shows that brand-focused keywords are more effective than non-brand-focused keywords (Jansen, Sobel, & Zhang, 2011). Using aggregated data, Rutz and Bucklin (2011) find spillover effects from generic to branded search engine advertising, whereas branded search does not affect generic search. Also, TV advertising for financial services brands heightens searchers’ tendency to use branded keywords instead of generic keywords by increasing their brand knowledge (Joo et al., 2014). It should be noted that the distinction between branded versus generic usage only applies to CICs; a corresponding differentiation is not possible for FICs, as customers do not actively trigger the contact.

Categorizing channels along the dimensions proposed above allows inferences on the underlying choice set formation processes. We suggest that subsequent clicks in different channel groups are a proxy for progress, especially if a store visitor switches from firm-initiated to customer-initiated channels: A potential customer who first visits the retailer's website through a firm-initiated channel and then comes back using a customer-initiated channel may be narrowing down his or her choice by actively searching for new information. A switch from FICs to a CIC should thus indicate a decrease in time to purchase. In contrast, staying within one channel group may be seen as a proxy for stagnation in the purchase decision process. Therefore, we do not expect meaningful interaction effects between clicks within the same channel group. Extending Rutz and Bucklin's (2011) argumentation that generic search advertisements serve to raise awareness that the brand is relevant to the search, a switch from generic to branded CICs may be a proxy for the fact that the advertiser's brand has been included in the consideration set and the customer is now looking for more detailed information.

4.3.2 Alternative Categorization Approaches

To test our categorization, we compare it against alternative categorization approaches proposed in the marketing literature. Relying on a taxonomy developed in information retrieval research, Klapdor (2013) proposes that channels should be categorized according to the user's assumed *browsing goal* in order to predict purchase propensities. A user's goal in Web search is of informational nature, if he or she wants "to learn something by reading or viewing web pages" (Rose & Levinson, 2004, p. 15). In contrast, the goal is navigational if the user wants to access a specific website (Broder, 2002). Correspondingly, channels such as type-in and email are categorized as navigational. If a user clicks on channels like display, price comparison, affiliate, and retargeting, he or she is assumed to be in information acquisition mode (Klapdor, 2013). Notwithstanding that this categorization improves the predictive power of a logistic regression model (Klapdor, 2013), inferences about a user's browsing goal are often ambiguous when drawn from the channel used: for example, depending on the context, a click on an email link does not necessarily have to be navigational.

In order to investigate channel effectiveness, Haan et al. (2013) propose that channels be categorized according to the *degree of content integration,* which measures the extent of advertising integration with website content. Content-integrated marketing activities are an integral part of the editorial content, whereas content-separated channels have no or little relation to the medium's content. Typical examples for content-integrated channels include price comparison websites or product placements in blogs (Zhu & Tan, 2007). A related concept currently gaining much attention among online marketing practitioners is so-called native advertising—sponsored content that looks like traditional editorial content (Vega, 2013). Other online marketing channels such as display or paid search are categorized as content-separated (Haan et al., 2013). Research shows that content-integrated channels are generally more effective than content-separated channels—potentially because they are less intrusive (Haan et al., 2013). However, while this categorization may help explain differences in the effectiveness of online channels, we do not expect to find meaningful interaction effects between channels along the customer journey, as the channel categories do not allow inferences on customers' choice set formation.

The *degree of personalization* (Haan et al., 2013) provides another possibility for categorizing channels. Internet marketing allows retailers to target customers individually (Pavlou & Stewart, 2000; Varadarajan & Yadav, 2009). The degree of personalization of an online channel describes whether the advertising message is individualized according to the characteristics or behavior(s) of the person being targeted (Haan et al., 2013). While nonpersonalized or mass marketing addresses a broad audience, personalized advertising explicitly targets customers according to individual characteristics. Because they are based on individual user queries (Ghose & Yang, 2009), both paid and organic search results are categorized as personalized. The same holds for retargeting banners, which display customized advertisements according to a user's prior surfing behavior (Lambrecht & Tucker, 2013). Similar to offline marketing channels, display and affiliate advertising are traditionally regarded as mass marketing channels (Verhoef et al., 2010). Again, this categorization is a useful tool for understanding differences in channel effectiveness, yet we do not expect it to help in analyzing the underlying purchase decision processes.

Table 11 provides an overview of the online channels presented above and their categorization. Unless noted otherwise, we follow the existing literature as closely as possible in our categorization.

Table 11

Categorization of Online Channels—Study 3

	Proposed categorization approach		Alternative categorizations		
Channel	Contact origin	Branded vs. generic usage	Browsing goal	Degree of content integration	Degree of personalization
Type-In	Customer-initiated	Branded	Navigation	Content-separated	Personalized
Branded Search	Customer-initiated	Branded	Navigation[a]	Content-separated	Personalized
Generic Search	Customer-initiated	Generic	Information[a]	Content-separated	Personalized
Price Comparison	Customer-initiated	Generic	Information	Content-integrated	Nonpersonalized
Display	Firm-initiated	–	Information	Content-separated	Nonpersonalized
Retargeting	Firm-initiated	–	Information	Content-separated	Personalized
Affiliate	Firm-initiated	–	Information	Content-integrated	Nonpersonalized
Email	Firm-initiated	–	Navigation	Content-separated	Nonpersonalized[b]

[a] In contrast to Klapdor (2013), we differentiate between navigational (branded) and informational (generic) search queries.

[b] While promotional emails are becoming increasingly customized (Ellis-Chadwick & Doherty, 2012), our data only include nonpersonalized email newsletters.

4.4 Methodology

4.4.1 Data

Our research is based on an individual-level data set provided by a German online fashion retailer and collected in collaboration with a multichannel tracking provider. The advertiser is an online-only retailer, so we do not have to account for online/offline cross-channel effects (Wiesel et al., 2011). As data collection started on the day the retailer's website and marketing campaigns were launched, there is no carryover from previous periods. The data were collected at the cookie level, so that we could identify individual users—or more accurately, individual devices. Although the use of cookie data suffers several limitations, such as an inability to track multidevice usage or a bias due to cookie deletion (Flosi et al., 2013; Rutz et al., 2011), cookies are currently the industry standard for multichannel tracking (Tucker, 2012).

For each website visit during the observation period, the data include detailed information about the channel used and an exact timestamp. We also know whether each contact was followed by a conversion—in this case a purchase transaction—and have information on past purchases. The online fashion retailer differentiates eight different online channels: SEA, SEO, display, email, price comparison, retargeting, type-in, and partner website. The retailer-specific channel “partner website” is defined as traffic coming from a virtual showroom run by an offline partner retailer. We categorize the partner website channel as content-integrated, nonpersonalized, informational, customer-initiated, and branded. The categorization of the other channels in our data set corresponds to Table 11. We differentiate paid and organic search (i.e., SEA and SEO) according to the keywords used: If the keyword contains the retailer’s brand or some spelling variant thereof, the search is branded; otherwise we speak of generic search.[16] As our study focuses on channel usage, we combine SEA and SEO, which both result from a search query. In an e-commerce context, searchers evaluate organic and sponsored results as similarly relevant (Jansen, Brown, & Resnick, 2007). In addition to all clicks across all channels, the data also include display views that do not directly lead to a click. For the other channels, tracking mere views is impossible for technical as well as legal reasons. For example, most large search engines do not provide information on views (Craver, 2013).

Our data set covers all users with at least one contact within a period of 45 days in spring 2013. In accordance with the usual cookie lifetime of the advertiser, we set the maximum journey length to 30 days. Journeys with more than 150 contacts, which were probably caused by bots, were excluded from the analyses. We used a random sample of 20% of all journeys, resulting in 343,722 individual journeys with a conversion rate of 3.1%. On average, a journey featured 2.9 contacts, which highlights the sparsity of our data. In Table 12, we present detailed descriptions of the journeys in our data set.

[16] Because we take the retailer’s perspective, we classify keywords containing product brands as generic.

Table 12

Descriptions (Fashion Retail)—Study 3

Description	N	Minimum	Maximum	Mean	Std. Dev.
Conversions	343,722	0	1	0.031	0.175
Past purchase	343,722	0	1	0.020	0.141
# Contacts in journey	343,722	1	150	2.929	5.609
# Clicks in branded CICs	343,722	0	124	0.871	1.756
# Clicks in generic CICs	343,722	0	81	0.402	1.051
# Clicks in FICs	343,722	0	80	0.657	0.798
# Clicks in navigational channels	343,722	0	124	0.935	1.815
# Clicks in informational channels	343,722	0	81	0.550	1.210
# Clicks in content-integrated channels	343,722	0	124	0.364	0.122
# Clicks in content-separated channels	343,722	0	117	1.121	1.686
# Clicks in personalized channels	343,722	0	117	0.958	1.650
# Clicks in nonpersonalized channels	343,722	0	124	0.528	1.336
# Display views	343,722	0	149	1.444	5.248
Duration (days)[a]	343,722	0	30	3.555	7.735

[a] Days between first and last contact.

4.4.2 Model Development

At a conversion rate of 3.1% within a 30-day window, the majority of our sample did not purchase within the observation period—although they might do so in the future. To reflect this right-censoring of the data and the sequential nature of customer journeys, we turn to proportional hazard models (Cox, 1972), which have already found application in online marketing research (Lambrecht & Tucker, 2013; Manchanda et al., 2006). As a survival analysis method, Cox regression measures the time it takes for an outcome to happen and calculates a hazard function. The Cox model does not make specific assumptions about the probability distribution of event times but assumes that the shape of the hazard function is the same for all groups over time (Cox, 1972). If this proportional hazards assumption is not met, Cox regression allows one to introduce time-dependent or time-varying covariates (Cai & Sun, 2003; Murphy & Sen, 1991; Tian, Zucker, & Wei, 2005), with values changing over time.

In our model, the dependent variable is the time to purchase. The hazard rate $h_i(t,X_t)$ for customer i is

$$h_i(t,X_t) = h_0(t)*\exp(X_{it}\beta), \quad (7)$$

where the base line hazard $h_0(t)$ covers the effect of time since the first observation. The vector of covariates X_{it} captures the advertising exposures on day t, past exposures, and the interaction effects—all as time-dependent variables. We define both channel-specific and aggregated variables to cover the number of clicks per channel (category) on day t and on the days preceding t. For example, the variable $SearchBranded_{it}$ corresponds with the number of searches for branded keywords leading to a website visit on a given day t. The variable $PastSearchBranded_{it}$ represents the cumulative number of branded search clicks by customer i before day t. We calculate the other channel-specific variables accordingly. In addition, we define aggregated variables as well as their lagged counterparts for each categorization approach:

- Contact origin + branded versus generic usage: $CICBranded_{it}$, $CICGeneric_{it}$, FIC_{it}, $PastCICBranded_{it}$, $PastCICGeneric_{it}$, and $PastFIC_{it}$
- Browsing goal: $Navigation_{it}$, $Information_{it}$, $PastNavigation_{it}$, and $PastInformation_{it}$
- Content integration: $Integrated_{it}$, $Separated_{it}$, $PastIntegrated_{it}$, and $PastSeparated_{it}$
- Personalization: $Personalized_{it}$, $Nonpersonalized_{it}$, $PastPersonalized_{it}$, and $PastNonpersonalized_{it}$

Besides website visits through different channels, we include the number of display advertising exposures in the variables $ViewsDisplay_{it}$ and $PastViewsDisplay_{it}$. These variables allow us to control for mere exposure effects of advertising (Janiszewski, 1993; Shapiro, MacInnis, & Heckler, 1997). Even if they do not lead to a click, ad exposures have a positive effect on repeat purchase probabilities (Manchanda et al., 2006). The number of display exposures can also serve as a control for activity bias (Lewis et al., 2011). Active browsers, who spend more time online, are more likely to see advertising—and are also more prone to buying online. Additionally, we account for past purchase, which is a well-established predictor of purchase probability (Moe & Fader, 2004; Poel & Buckinx, 2005), by adding it as a binary control variable. As a test for the proportionality of hazards indicates that past purchase does not meet the proportional hazard assumption, we include an interaction of past purchase with time in our models (Tabachnick & Fidell, 2012).

In Model 1a, which includes channel-specific variables and no interaction effects, we specify X_{it} as follows:

$$\exp(X_{it}\beta) = \exp(\beta_1 TypeIn_{it} + \beta_2 SearchBranded_{it} + \beta_3 PartnerWebsite_{it} + \beta_4 SearchGeneric_{it} + \beta_5 PriceComparison_{it} + \beta_6 Display_{it} + \beta_7 Retargeting_{it} + \beta_8 Email_{it} + \beta_9 PastTypeIn_{it} + \beta_{10} PastSearchBranded_{it} + \beta_{11} PastPartnerWebsite_{it} + \beta_{12} PastSearchGeneric_{it} + \beta_{13} PastPriceComparison_{it} + \beta_{14} PastDisplay_{it} + \beta_{15} PastRetargeting_{it} + \beta_{16} PastEmail_{it} + \beta_{17} ViewsDisplay_{it} + \beta_{18} PastViewsDisplay_{it} + \beta_{19} PastPurchase_i + \beta_{20} PastPurchase_i * t). \quad (8)$$

Because a categorization of channels is not necessary to investigate the main effects, we specify the nested models including interaction effects based on Model 1a, so as to avoid losing information. For the sake of completeness, we nevertheless test an aggregated main effects model (Model 1b):

$$\exp(X_{it}\beta) = \exp(\beta_1 CICBranded_{it} + \beta_2 CICGeneric_{it} + \beta_3 FIC_{it} + \beta_4 PastCICBranded_{it} + \beta_5 PastCICGeneric_{it} + \beta_6 PastFIC_{it} + \beta_7 ViewsDisplay_{it} + \beta_8 PastViewsDisplay_{it} + \beta_9 PastPurchase_i + \beta_{10} PastPurchase_i * t). \quad (9)$$

Using Model 1a as a basis, we add interaction effects between channel categories based on contact origin and branded versus generic usage in Model 2:

$$\exp(X_{it}\beta) = \exp(\beta_1 TypeIn_{it} + \beta_2 SearchBranded_{it} + \beta_3 PartnerWebsite_{it} + \beta_4 SearchGeneric_{it} + \beta_5 PriceComparison_{it} + \beta_6 Display_{it} + \beta_7 Retargeting_{it} + \beta_8 Email_{it} + \beta_9 PastTypeIn_{it} + \beta_{10} PastSearchBranded_{it} + \beta_{11} PastPartnerWebsite_{it} + \beta_{12} PastSearchGeneric_{it} + \beta_{13} PastPriceComparison_{it} + \beta_{14} PastDisplay_{it} + \beta_{15} PastRetargeting_{it} + \beta_{16} PastEmail_{it} + \beta_{17} ViewsDisplay_{it} + \beta_{18} PastViewsDisplay_{it} + \beta_{19} PastPurchase_i + \beta_{20} PastPurchase_{it} * t + \beta_{21} CICBranded_{it} * PastCICBranded_{it} + \beta_{22} CICGeneric_{it} * PastCICBranded_{it} + \beta_{23} FIC_{it} * PastCICBranded_{it} + \beta_{24} CICBranded_{it} * PastCICGeneric_{it} + \beta_{25} CICGeneric_{it} * PastCICGeneric_{it} + \beta_{26} FIC_{it} * PastCICGeneric_{it} + \quad (10)$$

$\beta_{27}CICBranded_{it}*PastFIC_{it} + \beta_{28}CICGeneric_{it}*PastFIC_{it} + \beta_{29}FIC_{it}*PastFIC_{it})$.

The alternative models follow the same logic as Model 2: Model 3 uses the browsing goal categorization; Model 4 includes the interaction effects between clicks in content-integrated and content-separated channels, whereas Model 5 investigates the interactions between clicks in personalized channels and reactions to mass marketing. We also specified a model including all possible two-way interactions on a channel level; however, this model does not converge due to the sparsity of the data.

4.5 Results

4.5.1 Model Comparison

Table 13 provides an overview of the goodness-of-fit results using log-likelihood, the Akaike Information Criterion (AIC; Akaike, 1974), and the Bayesian Information Criterion (BIC; Schwarz, 1978). Both AIC and BIC include a penalty that is an increasing function of the number of estimated parameters. Penalizing a loss in parsimony discourages overfitting and adjusts for the different number of parameters (Burnham & Anderson, 2002). As we use a censored survival model, we apply a revised version of the penalty term in BIC, such that it is defined in terms of the number of uncensored events instead of the number of observations (Volinsky & Raftery, 2000).

Overall, Model 2 shows the best model fit according to all three criteria, even though BIC generally tends to favor simpler models (Kass & Raftery, 1995). For the main effects, using channel-specific variables (Model 1a) increases the model fit compared to Model 1b, which confirms our decision to take Model 1a as the basis of our nested models (Models 2, 3, 4, and 5). Adding interaction effects between channel categories based on contact origin and branded versus generic usage (Model 2) significantly improves log-likelihood compared to the main effects model (Model 1a), $\chi^2(9, N = 343{,}722) = 148.747$, $p < .01$. The improvement in log-likelihood compared to Model 1a for Models 4 and 5 is significant (Model 4: $\chi^2(4, N = 343{,}722) = 41.556$, $p < .01$; Model 5: $\chi^2(4, N = 343{,}722) = 45.487$, $p < .01$), yet considerably lower than for Model 2. Model fit according to AIC is also lower for Models 4 and 5. A difference of > 10 in BIC compared to the other models provides strong evidence for the superiority of Model 2 (Kass & Raftery, 1995; Wasserman, 2000). For Model 3, the log-likelihood does not increase significantly compared to

Model 1a, and—after accounting for the number of parameters—the AIC and BIC values are even higher than in the more parsimonious model.

Table 13

Model Comparison (Fashion Retail)—Study 3

Characteristics	Model 1a	Model 1b	Model 2	Model 3	Model 4	Model 5
Categorization approach	No aggregation	Contact origin + branded vs. generic usage	Contact origin + branded vs. generic usage	Browsing goal	Content integration	Personali-zation
Main effects	Channels	Aggregated	Channels	Channels	Channels	Channels
Interaction effects	No interaction effects	No interaction effects	Aggregated	Aggregated	Aggregated	Aggregated
Measures						
Log-likelihood	-133,391	-133,981	-133,316	-133,387	-133,370	-133,368
AIC	266,821	267,982	266,690	266,822	266,787	266,784
BIC	266,967	268,055	266,901	266,997	266,962	266,959

4.5.2 Estimation Results

We present detailed estimation results for the nested Models 1a and 2 in Table 14. Because p-values can become artificially deflated for large samples, we not only report statistical significance but also 95% confidence intervals for the hazard ratios (Lin, M., Lucas, H. C., & Shmueli, G., 2013). While p-values do not scale up well, the information contained in confidence intervals becomes more precise with growing sample size (Lin, M. et al., 2013). In Model 1a, past purchase as a well-established predictor has the strongest positive effect on purchases (PastPurchase $b = 2.084$, $p < .01$). We find a significant positive interaction with time (PastPurchase × Time $b = 0.013$, $p < .01$), such that the purchase hazard increases with time. Current clicks in CICs (branded search, type-in, partner website, and generic search) positively predict purchases; the effect for price comparison is not significant. Website visits via email and retargeting also have a positive effect, whereas—compared to the other channels—display clicks have a negative impact on the immediate probability to purchase. Prior clicks in all channels except display decrease the time to purchase. Display clicks again are a negative predictor. To interpret these channel-specific coefficients, it is important to note that our data do not include information on users who do not see any ads or do not visit the retailer's website at all. Thus, channel coefficient estimates are relative: A negative coefficient for display does not necessarily mean that a user clicking on a display ad has a lower purchase propensity than someone without any advertising exposure. We can only conclude that display clicks have a negative effect compared to clicks in other channels. Display views do have a negative immediate but a positive lagged effect. The fact that a user does not click on a display ad may indicate limited immediate interest. Nevertheless, unclicked ads can have long-term effects: Mere exposure to advertising can influence consumers' consideration sets, even when they are not consciously aware of seeing the ads (Shapiro et al., 1997).

We find strong positive interaction effects between past clicks in FICs and clicks in CICs (CICBranded × PastFIC $b = 0.027$, $p < .01$; CICGeneric × PastFIC $b = 0.079$, $p < .01$). If a potential customer uses a CIC after having visited the website through a FIC, the probability of a same-day purchase increases significantly, especially after visits through CICGeneric. As assumed earlier, switches from firm-initiated to customer-initiated channels are a good proxy for progress in the consumer decision process. By using CICs, consumers actively search for more information—potentially to evaluate promising alternatives in their consideration set in more depth.

For switches between other channel groups, the results are less consistent and only significant at the .05 significance level: Clicks in CICBranded that are followed by current clicks in FICs positively predict purchase probability (FIC × PastCICBranded $b = 0.013$, $p < .05$). Contradicting prior research (Rutz & Bucklin, 2011), we find a small negative spillover effect from CICGeneric to CICBranded (CICBranded × PastCICGeneric $b = -0.006$, $p < .05$). Differences between retailer brands and product brands (Ghose & Yang, 2009) provide a potential explanation for these diverging results. In our case, branded search means that the keyword contains the retailer's brand name, whereas Rutz and Bucklin (2011) used data from a lodging chain (i.e., a product brand). The effects between FIC × PastCICGeneric and CICGeneric × PastCICBranded are not significant.

Interaction effects within channel groups are either not significant or show low effect sizes: We do not find significant interaction effects within CICGeneric. Interaction effects within clicks in CICBranded (CICBranded × PastCICBranded $b = -0.001$, $p < .01$) are negative and significant, although with a very small effect size. If followed by clicks in FICs, past clicks in FICs negatively predict the purchase probability of a consumer (FIC × PastFIC $b = -0.009$, $p < .05$), again with a small effect size. Thus, staying within one channel group does not positively impact purchase propensities and can therefore be used as a proxy for stagnation in the purchase decision process.

Table 14

Estimation Results (Fashion Retail)—Study 3

		Model 1a				Model 2			
Category	Variable	B	SE	Exp(B)	95% CI	B	SE	Exp(B)	95% CI
CIC Branded	TypeIn	0.080**	0.003	1.083	[1.077, 1.089]	0.081**	0.003	1.084	[1.078, 1.091]
	SearchBranded	0.210**	0.005	1.233	[1.221, 1.245]	0.211**	0.005	1.234	[1.222, 1.247]
	PartnerWebsite	0.140**	0.002	1.150	[1.144, 1.155]	0.138**	0.003	1.148	[1.142, 1.153]
CIC Generic	SearchGeneric	0.179**	0.009	1.196	[1.176, 1.217]	0.177**	0.009	1.194	[1.173, 1.215]
	PriceComparison	0.015	0.021	1.016	[0.974, 1.059]	0.009	0.023	1.009	[0.965, 1.054]
FIC	Display	-1.592**	0.106	0.204	[0.166, 0.250]	-1.594**	0.106	0.203	[0.165, 0.250]
	Retargeting	0.293**	0.020	1.341	[1.289, 1.395]	0.296**	0.023	1.345	[1.286, 1.406]
	Email	0.120**	0.026	1.127	[1.071, 1.186]	0.097*	0.038	1.102	[1.023, 1.186]
CIC Branded (Past)	PastTypeIn	0.056**	0.003	1.058	[1.051, 1.064]	0.057**	0.003	1.059	[1.052, 1.065]
	PastSearchBranded	0.057**	0.003	1.058	[1.052, 1.065]	0.058**	0.003	1.059	[1.053, 1.066]
	PastPartnerWebsite	0.050**	0.002	1.051	[1.047, 1.056]	0.051**	0.002	1.052	[1.047, 1.057]
CIC Generic (Past)	PastSearchGeneric	0.082**	0.006	1.086	[1.072, 1.100]	0.079**	0.008	1.082	[1.066, 1.099]
	PastPriceComparison	0.041*	0.019	1.041	[1.003, 1.082]	0.031	0.020	1.032	[0.992, 1.073]
FIC (Past)	PastDisplay	-0.923**	0.090	0.397	[0.333, 0.474]	-0.907**	0.089	0.404	[0.339, 0.481]
	PastRetargeting	0.152**	0.008	1.164	[1.145, 1.183]	0.132**	0.012	1.141	[1.114, 1.169]
	PastEmail	0.067**	0.008	1.069	[1.052, 1.086]	-0.033*	0.013	0.967	[0.942, 0.993]
Controls	ViewsDisplay	-0.034**	0.009	0.966	[0.950, 0.983]	-0.036**	0.009	0.965	[0.949, 0.981]
	PastViewsDisplay	0.024**	0.002	1.024	[1.020, 1.028]	0.024**	0.002	1.024	[1.020, 1.028]
	PastPurchase	2.084**	0.030	8.033	[7.568, 8.526]	2.076**	0.031	7.973	[7.509, 8.465]
	PastPurchase ×Time	0.013**	0.003	1.013	[1.007, 1.020]	0.014**	0.003	1.014	[1.008, 1.020]
Interaction effects	CICBranded × PastCICBranded					-0.001*	0.000	0.999	[0.999, 1.000]
	CICGeneric × PastCICBranded					-0.002	0.004	0.998	[0.991, 1.006]
	FIC × PastCICBranded					0.013*	0.005	1.013	[1.003, 1.023]
	CICBranded × PastCICGeneric					-0.006*	0.002	0.994	[0.990, 0.999]
	CICGeneric × PastCICGeneric					0.003	0.003	1.003	[0.997, 1.009]
	FIC × PastCICGeneric					0.016	0.008	1.016	[1.000, 1.033]
	CICBranded × PastFIC					0.027**	0.002	1.027	[1.023, 1.032]
	CICGeneric × PastFIC					0.079**	0.009	1.082	[1.062, 1.102]
	FIC × PastFIC					-0.009*	0.005	0.991	[0.982, 1.000]
	Observations	343,722				343,722			

Note. * p < .05, ** p < .01.

4.5.3 Robustness of Results

To test the robustness of our results and thus the generalizability of our theoretical reasoning, we run a similar analysis for a telecommunications service provider. We believe that using data from another industry is an even more conservative test than employing another retail data set: If the findings are robust across industries, they should also be robust within the retail business. The structure of the data set is equivalent to the data set presented above, in that we have detailed information on complete online customer journeys. The only difference is that this service provider employs six different online marketing channels: SEA, SEO, display, affiliate, retargeting, and type-in. Again, we can track each website visit during the observation period, including the channel used and an exact timestamp. As for the main data set, we also know whether there is an existing customer relationship and if a website visit leads to a conversion. However, unlike the online fashion retailer, the telecommunications service provider uses a multichannel sales strategy, including brick-and-mortar stores, direct marketing, and online. Unfortunately, we are unable to link offline conversions to online customer journeys.

The data set covers all users with at least one website visit within a period of 88 days in spring 2013. Akin to the data used earlier, we limited the maximum journey length to 30 days and excluded journeys with more than 150 contacts. The final data set includes 361,864 individual journeys with a conversion rate of 1.6% and an average length of 4.7 contacts. We present detailed descriptions of the data in Table 15.

Table 15

Descriptions (Telecommunications)—Study 3

Description	N	Minimum	Maximum	Mean	Std. Dev.
Conversions	361,864	0	1	0.016	0.127
Past purchase	361,864	0	1	0.009	0.095
# Contacts in journey	361,864	1	150	4.692	11.733
# Clicks in branded CICs	361,864	0	122	1.025	1.995
# Clicks in generic CICs	361,864	0	60	0.106	0.412
# Clicks in FICs	361,864	0	100	0.981	0.758
# Clicks in navigational channels	361,864	0	122	1.025	1.995
# Clicks in informational channels	361,864	0	100	0.495	0.927
# Clicks in content-integrated channels	361,864	0	49	0.149	0.481
# Clicks in content-separated channels	361,864	0	122	1.372	2.062
# Clicks in personalized channels	361,864	0	100	0.378	0.827
# Clicks in nonpersonalized channels	361,864	0	122	1.143	2.026
# Display views	361,864	0	149	3.172	11.327
Duration (days)[a]	361,864	0	30	4.298	8.723

[a] Days between first and last contact.

The models are analogous to the previous specification. In Table 16, we present the goodness-of-fit results. As for the main data set, Model 2 shows the best model fit according to all three criteria. Adding interaction effects between channel categories based on contact origin and branded versus generic usage (Model 2) significantly improves log-likelihood compared to the main effects model (Model 1a), $\chi^2(9, N = 361{,}864) = 187.180$, $p < .01$. Differences of >100 in BIC between Model 2 and the alternative models (Models 3, 4, and 5) are far above the threshold for strong evidence for model superiority (Kass & Raftery, 1995; Wasserman, 2000).

Table 16

Model Comparison (Telecommunications)—Study 3

Characteristics	Model 1a	Model 1b	Model 2	Model 3	Model 4	Model 5
Categorization approach	No aggregation	Contact origin + branded vs. generic usage	Contact origin + branded vs. generic usage	Browsing goal	Content integration	Personalization
Main effects	Channels	Aggregated	Channels	Channels	Channels	Channels
Interaction effects	No interaction effects	No interaction effects	Aggregated	Aggregated	Aggregated	Aggregated
Measures						
Log-likelihood	-70,439	-70,467	-70,346	-70,420	-70,429	-70,427
AIC	140,910	140,953	140,741	140,879	140,897	140,893
BIC	141,008	141,014	140,893	141,001	141,019	141,015

Table 17 shows the detailed estimation results for the nested Models 1a and 2. Overall, we can confirm the direction of most channel-specific effects in Model 1a. As in the fashion retail data set, past purchase as a well-established predictor has the strongest positive effect on purchases (PastPurchase $b = 3.981$, $p < .01$). The effect of past purchase is time-dependent, although the direction of the effect seems industry specific. Whereas the purchase hazard increases with time for the fashion retailer, we find an opposite effect for the telecommunications provider (PastPurchase × Time $b = -0.043$, $p < .01$). Differences in purchase frequency are a potential explanation: consumers buy fashion items rather frequently, whereas telecommunications services mostly require long-term contracts. Current clicks in branded CICs (branded search and type-in) again predict purchases in a positive way; the effect for generic search is not significant. Compared to the other channels, display clicks have a negative impact on the immediate probability to purchase, whereas website visits via affiliate and retargeting have a positive effect. As in the other data set, prior clicks in all channels except display decrease the time to purchase and display views do have a negative immediate but a positive lagged effect.

The robustness check confirms strong positive interaction effects between past clicks in FICs and clicks in CICs (CICBranded × PastFIC $b = 0.137$, $p < .01$; CICGeneric × PastFIC $b = 0.162$, $p < .01$), indicating progress in the purchase decision process. As in the first data set, interaction effects within channel groups show low effect sizes compared to switches from FICs to CICs: Interaction effects within clicks in CICBranded (CICBranded × PastCICBranded $b = -0.012$, $p < .01$) are negative, yet with a small effect size. The positive interaction effect of subsequent clicks within CICGeneric is significant at the 5% level (CICGeneric × PastCICGeneric $b = 0.043$, $p < .05$). If followed by clicks in FICs, previous clicks in FICs have a small positive interaction effect (FIC × PastFIC $b = 0.022$, $p < .01$). While the direction of effects is not always identical compared to the fashion retail data, the effect sizes of within-channel effects are smaller in both cases than any of the significant between-channel effects.

Results for the other between-channel interactions differ between the two data sets. For the telecommunications provider, past clicks in CICGeneric followed by website visits through other channel types increase the probability of a conversion (CICBranded × PastCICGeneric $b = 0.087$, $p < .01$; FIC × PastCICGeneric $b = 0.537$, $p < .01$). In contrast, clicks in CICBranded that are followed by current clicks in FICs negatively predict purchase probability (FIC × PastCICBranded $b = -0.065$, $p < .01$). Besides the above-mentioned distinction between product and retailer brands, these differences might also be due to diverging marketing strategies—for example, regarding the design and content of retargeting ads (Lambrecht & Tucker, 2013).

Table 17

Estimation Results (Telecommunications)—Study 3

		Model 1a				Model 2			
Category	Variable	B	SE	Exp(B)	95% CI	B	SE	Exp(B)	95% CI
CIC Branded	TypeIn	0.076 **	0.004	1.079	[1.071, 1.087]	0.075 **	0.004	1.078	[1.070, 1.086]
	SearchBranded	0.152 **	0.011	1.164	[1.139, 1.190]	0.147 **	0.011	1.158	[1.133, 1.184]
CIC Generic	SearchGeneric	-0.062	0.055	0.940	[0.843, 1.047]	-0.095	0.056	0.909	[0.815, 1.014]
FIC	Display	-0.126 **	0.043	0.881	[0.809, 0.960]	-0.138 **	0.043	0.871	[0.800, 0.948]
	Retargeting	0.106 **	0.029	1.112	[1.050, 1.178]	0.102 **	0.033	1.107	[1.038, 1.181]
	Affiliate	0.138 **	0.007	1.148	[1.131, 1.164]	0.136 **	0.008	1.146	[1.129, 1.163]
CIC Branded (Past)	PastTypeIn	0.073 **	0.005	1.076	[1.066, 1.086]	0.059 **	0.008	1.061	[1.043, 1.078]
	PastSearchBranded	0.064 **	0.007	1.066	[1.052, 1.081]	0.075 **	0.009	1.078	[1.058, 1.098]
CIC Generic (Past)	PastSearchGeneric	0.091 *	0.043	1.096	[1.006, 1.193]	-0.081	0.072	0.922	[0.800, 1.063]
FIC (Past)	PastDisplay	-0.136 **	0.050	0.873	[0.792, 0.962]	-0.208 **	0.052	0.812	[0.733, 0.899]
	PastRetargeting	0.134 **	0.021	1.143	[1.098, 1.191]	0.133 **	0.024	1.142	[1.090, 1.196]
	PastAffiliate	0.142 **	0.010	1.152	[1.129, 1.176]	0.070 *	0.032	1.073	[1.007, 1.144]
Controls	ViewsDisplay	-0.064 **	0.009	0.938	[0.922, 0.954]	-0.065 **	0.009	0.937	[0.921, 0.953]
	PastViewsDisplay	0.031 **	0.001	1.031	[1.029, 1.033]	0.031 **	0.001	1.031	[1.029, 1.034]
	PastPurchase	3.981 **	0.031	53.595	[50.428, 56.961]	3.975 **	0.031	53.242	[50.096, 56.586]
	PastPurchase ×Time	-0.043 **	0.006	0.958	[0.948, 0.969]	-0.042 **	0.006	0.959	[0.949, 0.970]
Inter-action effects	CICBranded × PastCICBranded					-0.012 **	0.004	0.989	[0.982, 0.995]
	CICGeneric × PastCICBranded					0.024	0.023	1.024	[0.978, 1.072]
	FIC × PastCICBranded					-0.065 **	0.008	0.937	[0.922, 0.953]
	CICBranded × PastCICGeneric					0.087 **	0.029	1.091	[1.031, 1.154]
	CICGeneric × PastCICGeneric					0.043 *	0.018	1.043	[1.008, 1.080]
	FIC × PastCICGeneric					0.537 **	0.056	1.711	[1.535, 1.908]
	CICBranded × PastFIC					0.137 **	0.015	1.147	[1.114, 1.180]
	CICGeneric × PastFIC					0.162 **	0.042	1.176	[1.084, 1.276]
	FIC × PastFIC					0.022 **	0.004	1.022	[1.014, 1.030]
	Observations	361,864				361,864			

Note. * p < .05, ** p < .01.

4.6 Discussion and Outlook

In this study, we developed and tested a model to analyze multichannel online customer journeys. While prior research on categorizing online channels has mainly focused on comparing their effectiveness (Haan et al., 2013; Li & Kannan, 2014; Wiesel et al., 2011), we categorize online channels to understand if and how channel usage along the customer journey allows inferences on the underlying purchase decision process. By differentiating online channels along the dimensions of contact origin and branded versus generic usage, we find interaction effects between contacts across channel types using two data sets from different industries. The estimation results support our argumentation based on the theory of choice sets: A switch from FICs to CICs, and especially to generic CICs, seems to be a good proxy for progress in the purchase decision process. In contrast, sequences of contacts within the same channel group do not allow meaningful inferences on purchase probabilities. The model fit is significantly improved when including interactions between the proposed channel categories, whereas alternative categorizations have lower explanatory power or do not even justify the inclusion of interaction effects.

Our research contributes to marketing theory and practice in a number of ways. First, we contribute to research on consumer decision-making by successfully applying the theory of choice sets (Hauser & Wernerfelt, 1990; Shocker et al., 1991; Spiggle & Sewall, 1987) in an online retail context. In this way, we respond to Yadav and Pavlou's (2014) call for a reinvestigation of existing theoretical approaches, given that marketing practitioners claim that online channels have fundamentally changed consumer decision processes (Court et al., 2009; Edelman, 2010). Although awareness and consideration sets are not directly observable in field data (Shocker et al., 1991), our results show that the theory of choice sets provides a valuable basis for interpreting interaction effects between online channels. Interaction effects between contacts across channel types indicate an increase in purchase propensity and thus serve as a good proxy for progress in multistage purchase decision processes.

Second, we contribute to research on multichannel online marketing by developing and testing a categorization approach that is able to handle sparse multidimensional data. Without categorizing channels, a detailed analysis of interaction effects along the customer journey is not feasible due to the sparsity of real-life multichannel clickstream data. The categorization we propose outperforms alternative categorizations found in the literature, namely the inferred browsing goal

(Klapdor, 2013), the degree of content integration, and the degree of personalization (Haan et al., 2013). In addition, the proposed distinction along contact origin and branded versus generic usage easily accommodates channel evolution and is less ambiguous than alternative categorizations. For example, inferring a customer's browsing goal from channel usage is often debatable. For display advertising, a clear distinction according to the degree of personalization becomes increasingly difficult with the ascent of behavioral targeting (Schumann et al., 2014). An unambiguous differentiation between categories is of special importance in the online retailing environment, where the relevance of channels "waxes and wanes, as new channels/media emerge and existing channels/media metamorphose into new forms" (Dholakia et al., 2010, p. 94).

Third, we advance research on channel effectiveness in a multichannel setting. The existence of meaningful and significant interaction effects along the customer journey adds to previous claims that analyzing channels in isolation may lead to wrong conclusions and suboptimal managerial decisions (Li & Kannan, 2014; Xu et al., 2014). Simple heuristics such as "last click wins," which are still employed by many advertisers (Econsultancy, 2012b; The CMO Club & Visual IQ, Inc., 2014), offer a distorted view of online marketing effectiveness. However, even more sophisticated attribution models, which do not account for interaction effects among channels (e.g., Danaher & Dagger, 2013; Haan et al., 2013), do not cover the full complexity of consumer decision processes.

Fourth, our research helps to close the gap between online marketing research and practice. Whereas Yadav and Pavlou (2014) lament that current marketing research does not fully capture the increasing richness and complexity of firms' online marketing activities, our approach for analyzing customer journeys covers the full spectrum of online channels available to marketers. With few recent exceptions (Anderl et al., 2014; Klapdor, 2013; Li & Kannan, 2014), research investigating more than two or three online channels in parallel is rare. Compared to prior studies on multichannel online marketing (Abhishek et al., 2012; Breuer et al., 2011; Kireyev et al., 2013; Lewis & Nguyen, 2014; Nottorf, 2014; Papadimitriou et al., 2011; Xu et al., 2014), our study—which considers eight different channels—provides a much more realistic picture of multichannel online marketing.

Fifth, our findings have important implications for real-time bidding and can help retailers develop individualized marketing and targeting strategies based on contact histories. When bidding for an available ad space, marketers should take into account the previous customer journey: The channels employed by the user are as important to know as whether said user has previously visited the website. The model and the categorization we provide are useful tools for assessing the purchase propensity of individual users and can serve as a basis for developing bidding strategies. For example, search engine providers have recently started to offer retargeting solutions, such that advertisers can tailor their bids on keywords for previous website visitors (Google Inc., 2014). Given our results, a customer who has previously clicked on FICs warrants a higher bid on generic keywords than a customer who has used a branded CIC to reach the website. In addition, managers can also use customer journey information to customize landing pages for users in different stages of the purchase decision process. For instance, firms could position information on shipping options more prominently for consumers using CICs if they have already visited through FICs in the past.

Like any research, this study is subject to limitations that provide avenues for future research. First, although cookies are the industry standard for multichannel tracking (Tucker, 2012), this way of collecting data has several disadvantages, such as bias due to cookie deletion (Flosi et al., 2013; Rutz et al., 2011). Additionally, cookies cannot identify either the use of the same computer by multiple consumers or the use of multiple devices by a single consumer (Flosi et al., 2013). To resolve these issues, marketing research should work on developing alternative approaches to collecting individual-level user data, such as digital fingerprinting (Nikiforakis et al., 2013). Second, information on views that do not directly lead to a click is only available for display advertising for technical and legal reasons. For example, most large search engines have recently introduced encrypted search, thereby considerably limiting the information available to advertisers (Craver, 2013). Although our data set reflects the actual information available to most online retailers, we are limited in our ability to use said data for generalizing on the effectiveness of advertising exposures; thus, we only included ad exposures as a control. Third, our use of real-life field data does not allow us to distinguish causality from correlation. There may be alternative explanations for the effectiveness of certain channels, such as the selective targeting of customers with inherently higher purchase propensity. Although we control for the number of advertising exposures in FICs, there still remains a possibility of activity bias (Lewis et al., 2011). We therefore focused on predicting purchase propensities based on website visits through various channels and establishing a theoretically substantiated categorization of online channels. However, it would be very interesting to analyze the interplay of channels using large-scale field experiments in order to establish causal relationships. Though such experiments would be very hard to implement in an online multichannel setting, especially when investigating the interplay of more than two channels, they would be a valuable addition to our research.

5 Conclusion

This dissertation addresses three major marketing challenges emerging in the digital economy, namely new business models, a proliferation of touchpoints and channels, and big data, in three independent studies: Study 1 focuses on nonmonetary customer value contributions in free e-services and thus explores emerging business models in the network economy. Studies 2 and 3 investigate the analysis of multichannel online consumer behavior in times of big data.

5.1 Implications

The three studies presented in this dissertation contribute to marketing theory and practice in a number of ways. Study 1 investigates nonmonetary customer value contributions in the context of free e-services based on an extensive literature review and qualitative interviews with industry experts. Our findings make several contributions: First, we conceptualize attention and data as two new NMCVC dimensions that have so far been disregarded in research on customer value. Both attention and data are core constituents of many free e-service business models but also extend beyond the free e-service domain. Second, we contribute to research on customer engagement by exploring the definitional boundaries of customer engagement behaviors. Prior research has defined CEBs as voluntary behaviors with a brand or firm focus resulting from motivational drivers (Brodie et al., 2011; Jaakkola & Alexander, 2014; Kumar, Aksoy et al., 2010; van Doorn et al., 2010). The fact that a clear distinction between motivational and nonmotivational behaviors is not always possible for attention and data limits the discriminatory power of the existing CEB definitions, thereby providing several opportunities for future research and theory refinement. Third, we contribute to research on the growing free e-service industry by explicating the nature and dynamics of NMCVCs in free e-services. Besides identifying attention and data as additional dimensions, we confirm WOM, co-production, and network effects as important NMCVCs in free e-services. In addition, we extend existing knowledge on co-production and network effects. Fourth, our findings contribute to research on value co-creation in networked environments in SDL (Lusch & Vargo, 2006; Vargo & Lusch, 2008). Kuppelwieser et al. (2013) call for a reexamination of SDL because the free e-service industry seems to undermine the generalizability of selected foundational premises. Our exhaustive analysis of value creation in free e-services establishes a basis for theory refinement in this special context. Fifth, understanding NMCVCs and their business outcomes in more detail increases managerial awareness for the value of nonpaying customers and thus facilitates active customer relationship management.

In Study 2, we address the attribution challenge, which online marketers confront, by introducing a new graph-based framework to analyze multichannel online customer journey data as first- and higher-order Markov walks. To increase practical acceptance, we develop a comprehensive set of criteria for attribution models, embracing both scientific rigor and practical applicability. Using four, large, real-world data sets from different industries, we evaluate four different model variations and compare our results to widely-used heuristic approaches. We find substantial differences to existing approaches and thus provide a practice-oriented alternative to often misleading attribution heuristics. Furthermore, the variation in our results demonstrates that insights into channel effectiveness should not be generalized from single data sets. By providing a set of evaluation criteria, we reduce the thresholds for applying and selecting attribution techniques in managerial practice, in order to foster standardization and cross-industry acceptance (Dalessandro et al., 2012). Our study responds to research requests to develop marketing impact models and techniques based on individual-level, single-source data (Rust, Lemon et al., 2004) and provides a new perspective on analyzing path data in marketing (Hui et al., 2009). From a managerial perspective, our research facilitates an objective and independent logic for deriving budget optimization processes and strategic decisions. The framework we propose can update the mental models of decision makers and—being purely data driven—affect organizations such that it reduces hierarchies and consecutively improves team decisions (Lilien, 2011). The versatility of our framework makes it suitable across industries and marketing contexts and allows for future applications.

In Study 3, we develop and test a model for analyzing multichannel online customer journeys in order to investigate how channel usage facilitates inferences on underlying purchase decision processes. Our research contributes to marketing theory and practice in at least five ways: First, we answer the call to reinvestigate existing marketing theory in the Internet environment (Yadav & Pavlou, 2014) by finding support for the theory of choice sets (Hauser & Wernerfelt, 1990; Shocker et al., 1991; Spiggle & Sewall, 1987) in an online context. Second, we present a new approach to overcome the curse of dimensionality in multichannel clickstream data. The categorization we propose outperforms alternative approaches (Haan et al., 2013; Klapdor, 2013) and permits the identification of meaningful interaction effects between contacts across channel types. Third, our results further substantiate claims that analyzing channels in isolation may lead to erroneous conclusions on channel effectiveness (Li & Kannan, 2014; Xu et al., 2014). Fourth, we help close the gap between online marketing research and practice (Yadav & Pavlou, 2014) by offering a realistic picture of channel diversity: In contrast to existing research on multichannel online marketing, which mainly focuses on the interplay of selected channels, we include eight different channels in our analysis. Fifth, our results can find application in real-time bidding in ad exchanges (Muthukrishnan, 2009) by helping retailers develop individualized targeting strategies based on contact histories.

Taking a broader perspective, this dissertation emphasizes the benefits of methodological diversity in marketing research by using a variety of methods including qualitative interviews, Markov graphs, and survival models. Whereas structural equation modeling based on survey data long seemed to be the dominant approach in interactive marketing research (Hofacker, 2012), other methodologies such as qualitative interviews—as used in Study 1—or netnography (Kozinets, 2002) can shed new light on emerging issues (Hennig-Thurau, Hofacker, & Bloching, 2013). Bringing in new techniques from related disciplines, such as simulations or data mining, can provide valuable insights into complex problems (Yadav & Pavlou, 2014). Study 2 provides an example of how to use graph-based data mining techniques to address marketing problems of high managerial relevance. Despite the appeal of new approaches, marketing theory is essential to provide generalizability and efficient ways of understanding (Rust, 2006), which we exemplify in Study 3.

Additionally, we add to the long debate on practical relevance versus rigor in marketing and management research (Danneels & Lilien, 1998; Gulati, 2007). Marketing scientists have recently rekindled this discussion (Jaworski, 2011; Lehmann et al., 2011; Lilien, 2011; Reibstein et al., 2009), lamenting that "there is an alarming and growing gap between the interests, standards, and priorities of academic marketers and the needs of marketing executives operating in an ambiguous, uncertain, fast-changing, and complex marketspace" (Reibstein et al., 2009, p. 1). By interviewing senior executives of free e-services in Study 1, we ensure a focus on questions of high managerial relevance. Both Studies 2 and 3 develop new approaches to handle high-dimensional multichannel online marketing data that are accessible to marketing managers while adhering to the standards of analytical rigor. Thus, this dissertation responds to the call for a renewed dual-focus on rigor and relevance of research (Roberts, Kayande, & Stremersch, 2014).

5.2 Outlook

Looking ahead, this dissertation identifies a number of promising avenues for future research, which we summarize in this section. A more detailed and specific discussion of future research opportunities can be found in the respective studies.

The setup of Study 1, which is based on qualitative interviews with senior executives of free e-service providers, offers at least two opportunities for further research: First, an empirical validation could reconfirm the findings of our qualitative study on a larger scale and create a link between managerial perceptions of NMCVCs and performance measures for the business success of free e-service providers. Second, our study mainly represents the managerial view on NMCVCs in free e-services. Further research should integrate the customer perspective and examine whether and to what extent customers are actually aware of contributing value to free e-services. Understanding the customer perspective can lead to a better alignment of value creation processes and help to clarify the ambiguous, semi-motivational nature of attention and data.

The clickstream data sets used in Studies 2 and 3 suffer from several limitations that could motivate further research. Although cookies are the industry standard for multichannel tracking (Tucker, 2012), this way of collecting data has several disadvantages (Chatterjee et al., 2003; Flosi et al., 2013; Rutz et al., 2011). Most importantly, cookie data may suffer from bias due to cookie deletion (Flosi et al., 2013). Additionally, cookies can neither identify the use of the same computer by multiple consumers nor the use of multiple devices usage by a single consumer (Flosi et al., 2013). As this problem is gaining importance with the uptake of mobile Internet usage (Winterberry Group, 2013), marketing research should work on developing alternative approaches to collecting individual-level user data, such as digital fingerprinting (Nikiforakis et al., 2013).

Outside of a few exceptions (Abhishek et al., 2012; Li & Kannan, 2014; Nottorf, 2014; Xu et al., 2014), multichannel online advertising research that incorporates not only clickstream data but also individual-level exposures that do not directly lead to a click is rare. Integrating this information—as we do in Study 3—could help to gain an even better understanding of online marketing effectiveness. Unfortunately, data availability is still limited. For technical and legal reasons we only have access to views in selected channels, such that we only include ad exposures as a control variable. Integrating this information in future studies would improve the generalizability of results. A replication of our studies with data from other companies or industries would be another important step toward empirical generalizations. Although we validate our results on data sets from different industries in Studies 2 and 3, some of our findings still might be company specific.

Finally, the long debate on correlation versus causation has been rekindled in the context of big data (Brown, Chui, & Manyika, 2011; Cukier & Mayer-Schönberger, 2013; McAfee & Brynjolfsson, 2012). A strict causal interpretation of customer journey field data is difficult, because alternative explanations for correlations between advertising exposures and conversions may exist. Observed correlations might be due to selection effects, such as activity bias (Lewis et al., 2011) or the explicit targeting of customers who have a higher propensity to purchase (Lambrecht & Tucker, 2013). In this case, advertising may appear to attract consumers who would have found other channels to visit the company's website (Blake, Nosko, & Tadelis, 2014). Both Study 2 and Study 3 therefore refrain from demonstrating causality. To establish a strict causal relationship between advertising and individual purchase behavior, large-scale field experiments or quasi-experiments with randomized exposure are required. Examples for such experiments include studies by Blake et al. (2014), Lambrecht and Tucker (2013), Lewis and Nguyen (2014), and Papadimitriou et al. (2011). Though controlled experiments are very hard to implement in an online multichannel setting, especially when investigating the interplay of more than two channels, these would be a valuable addition to our research.

The research opportunites discussed above mainly pertain to the online world. Furthermore we identify several avenues for further research that extend beyond the digital economy, which also suggests that the challenges identified in Chapter 1 are no longer exclusive to the digital domain. The offline relevance of our research on free e-service business models is twofold: On the one hand, business models that involve offering a product or service for free are spreading beyond the digital realm (Bryce et al., 2011). On the other hand, NMCVCs also play an important role in non-free business models, as shown in customer engagement literature (Brodie et al., 2011; Jaakkola & Alexander, 2014; Kumar, Aksoy et al., 2010; van Doorn et al., 2010; Verleye et al., 2014). Further research should therefore investigate the broader applicability of our findings using the free e-service industry as a magnifying glass that highlights important new aspects of value creation and customer engagement.

The proliferation of channels is again not limited to the online world. Many firms use online and offline channels in parallel (Raman et al., 2012), especially in times of media multiplexing (Lin, C., Venkataram, S., & Jap, S. D., 2013). Prior research on synergies between online and offline channels is mostly based on aggregated data (Joo et al., 2014; Naik & Peters, 2009) or laboratory experiments (Chang & Thorson, 2004; Dijkstra, Buijtels, & Vanraaij, 2005; Voorveld, Neijens, & Smit, 2011). Studies investigating the interplay of multiple online and offline marketing channels on an individual consumer level are rare—mainly due to limited data availability (Bollinger et al., 2013; Danaher & Dagger, 2013; McDonald, Wilson, & Konuş, 2012). Marketing researchers and practitioners should look for ways to expand the approaches presented in this dissertation in order to measure and analyze online and offline channels simultaneously.

Finally, “big data is distinct from the Internet” (Cukier & Mayer-Schönberger, 2013), even though the Internet facilitates data collection. The “Internet of Things” (Atzori, Iera, & Morabito, 2010, p. 2787), i.e. sensor-based Internet-enabled devices equipped with radio frequency identification (RFID), barcodes, and radio tags, opens up new data-driven research opportunities (Chen et al., 2012). For example, smart meters measure individual consumption patterns for energy and water (Farhangi, 2010). RFID technology can track consumers’ grocery store shopping paths (Hui et al., 2009), thus enabling an analysis of offline customer journeys. In summary, “datafication,” that is the ability to quantify phenomena that have previously been unamenable to measurement (Cukier & Mayer-Schönberger, 2013), offers ample opportunities for future research on analyzing and managing consumer behavior—both online and offline.

6 References

Abhishek, V., Fader, P. S., & Hosanagar, K. (2012). *Media exposure through the funnel: A model of multi-stage attribution*. Retrieved from http://ssrn.com/abstract=2158421

Abou Nabout, N., Lilienthal, M., & Skiera, B. (2014). Empirical generalizations in search engine advertising. *Journal of Retailing*, *90*(2), 206–216. doi:10.1016/j.jretai.2014.03.002

Abou Nabout, N., Skiera, B., Stepanchuk, T., & Gerstmeier, E. (2012). An analysis of the profitability of fee-based compensation plans for search engine marketing. *International Journal of Research in Marketing*, *29*(1), 68–80. doi:10.1016/j.ijresmar.2011.07.002

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, *17*(6), 734–749. doi:10.1109/TKDE.2005.99

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. doi:10.1109/TAC.1974.1100705

Albuquerque, P., Pavlidis, P., Chatow, U., Chen, K.-Y., & Jamal, Z. (2012). Evaluating promotional activities in an online two-sided market of user-generated content. *Marketing Science*, *31*(3), 406–432. doi:10.1287/mksc.1110.0685

Algesheimer, R., & Wangenheim, F. von (2006). A network based approach to customer equity management. *Journal of Relationship Marketing*, *5*(1), 39–57. doi:10.1300/J366v05n01_04

Allenby, G. M., & Rossi, P. E. (1999). Marketing models of consumer heterogeneity. *Journal of Econometrics*, *89*(1), 57–78. doi:10.1016/S0304-4076(98)00055-4

Anderl, E., Becker, I., Wangenheim, F. von, & Schumann, J. H. (2014). *Mapping the customer journey: A graph-based framework for online attribution modeling*. Retrieved from http://ssrn.com/abstract=2343077

Anderson, C. (2009). *Free. The future of a radical price*. New York, NY: Hyperion.

Ansari, A., & Mela, C. F. (2003). E-customization. *Journal of Marketing Research*, *40*(2), 131–145. doi:10.1509/jmkr.40.2.131.19224

Ansari, A., Mela, C. F., & Neslin, S. A. (2008). Customer channel migration. *Journal of Marketing Research*, *45*(1), 60–76. doi:10.1509/jmkr.45.1.60

Archak, N., Mirrokni, V. S., & Muthukrishnan, S. (2010). Mining advertiser-specific user behavior using adfactors. In M. Rappa & P. Jones (Eds.), *Proceedings of the 19th International Conference on World Wide Web* (pp. 31–40). ACM.

Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, *54*(15), 2787–2805. doi:10.1016/j.comnet.2010.05.010

Bakos, Y., & Katsamakas, E. (2008). Design and ownership of two-sided networks: Implications for Internet platforms. *Journal of Management Information Systems*, *25*(2), 171–202. doi:10.2753/MIS0742-1222250208

Bawa, K., & Shoemaker, R. (2004). The effects of free sample promotions on incremental brand sales. *Marketing Science*, *23*(3), 345–363. doi:10.1287/mksc.1030.0052

Bellman, R. E. (1961). *Adaptive control processes: A guided tour*. Princeton, NJ: Princeton University Press.

Berchtold, A., & Raftery, A. E. (2002). The mixture transition distribution model for high-order Markov chains and non-Gaussian time series. *Statistical Science*, *17*(3), 328–356. doi:10.1214/ss/1042727943

Berman, R. (2013). *Beyond the last touch: Attribution in online advertising*. Retrieved from http://ron-berman.com/papers/attribution.pdf

Bijmolt, T. H. A., Leeflang, P. S. H., Block, F., Eisenbeiss, M., Hardie, B. G. S., Lemmens, A., & Saffert, P. (2010). Analytics for customer engagement. *Journal of Service Research*, *13*(3), 341–356. doi:10.1177/1094670510375603

Blake, T., Nosko, C., & Tadelis, S. (2014). *Consumer heterogeneity and paid search effectiveness: A large scale field experiment* (NBER Working Paper). Retrieved from faculty.haas.berkeley.edu/stadelis/Tadelis.pdf

Bodapati, A. V. (2008). Recommendation systems with purchase data. *Journal of Marketing Research*, *45*(1), 77–93. doi:10.1509/jmkr.45.1.77

Bollinger, B., Cohen, M., & Jiang, L. (2013). *Measuring asymmetric persistence and interaction effects of media exposures across platforms*. Retrieved from http://ssrn.com/abstract=2342349

Boston Consulting Group. (2012). It keeps growing … and growing … *Harvard Business Review*, (10), 32–34.

Boudreau, K. J., & Jeppesen, L. B. (2014). Unpaid platform complementors and the network effect mirage. *Strategic Management Journal*, *forthcoming*.

Bradley, A. P. (1997). The use of the area under the ROC curve in the evaluation of machine learning algorithms. *Pattern Recognition*, *30*(7), 1145–1159. doi:10.1016/S0031-3203(96)00142-2

Braun, M., & Moe, W. W. (2013). Online display advertising: Modeling the effects of multiple creatives and individual impression histories. *Marketing Science*, *32*(5), 753–767. doi:10.1287/mksc.2013.0802

Breuer, R., Brettel, M., & Engelen, A. (2011). Incorporating long-term effects in determining the effectiveness of different types of online advertising. *Marketing Letters*, *22*(4), 327–340. doi:10.1007/s11002-011-9136-3

Breuer, R., & Brettel, M. (2012). Short- and long-term effects of online advertising: Differences between new and existing customers. *Journal of Interactive Marketing*, *26*(3), 155–166. doi:10.1016/j.intmar.2011.12.001

Broder, A. (2002). A taxonomy of Web search. *ACM SIGIR Forum*, *36*(2), 3–10. doi:10.1145/792550.792552

Brodie, R. J., Hollebeek, L. D., Juric, B., & Ilic, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research*, *14*(3), 252–271. doi:10.1177/1094670511411703

Bronnenberg, B. J. (1998). Advertising frequency decisions in a discrete Markov process under a budget constraint. *Journal of Marketing Research*, *35*(3), 399–406. doi:10.2307/3152037

Brousseau, E., & Penard, T. (2007). The economics of digital business models: A framework for analyzing the economics of platforms. *Review of Network Economics*, *6*(2), 81–114. doi:10.2202/1446-9022.1112

Brown, B., Chui, M., & Manyika, J. (2011). Are you ready for the era of 'big data'? *McKinsey Quarterly*, *4*, 24–35. Retrieved from http://www.mckinsey.com/insights/strategy/are_you_ready_for_the_era_of_big_data

Brown, S., Kozinets, R. V., & Sherry, J. F., Jr. (2003). Teaching old brands new tricks: Retro branding and the revival of brand meaning. *Journal of Marketing*, *67*(3), 19–33. doi:10.1509/jmkg.67.3.19.18657

Bruggen, G. H. van, Smidts, A., & Wierenga, B. (1998). Improving decision making by means of a marketing decision support system. *Management Science*, *44*(5), 645–658. doi:10.1287/mnsc.44.5.645

Bryce, D. J., Dyer, J. H., & Hatch, N. W. (2011). Competing against free. *Harvard Business Review*, *89*(6), 104–111.

Brynjolfsson, E., & Oh, J. (2012). The attention economy: Measuring the value of free digital services on the Internet. In F. G. Joey (Ed.), *Proceedings of the 33rd International Conference on Information Systems.*

Bucklin, R. E., & Sismeiro, C. (2009). Click here for Internet insight: Advances in clickstream data analysis in marketing. *Journal of Interactive Marketing*, *23*(1), 35–48. doi:10.1016/j.intmar.2008.10.004

Bughin, J., Shenkan, A. G., & Singer, M. (2008). How poor metrics undermine digital marketing. *The McKinsey Quarterly*, *4*, 38–61.

Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multimodel inference: A practical information-theoretic approach* (2nd ed.). New York, NY: Springer.

Cai, Z., & Sun, Y. (2003). Local linear estimation for time-dependent coefficients in Cox's regression models. *Scandinavian Journal of Statistics*, *30*(1), 93–111. doi:10.1111/1467-9469.00320

Casadesus-Masanell, R., & Zhu, F. (2013). Business model innovation and competitive imitation: The case of sponsor-based business models. *Strategic Management Journal*, *34*(4), 464–482. doi:10.1002/smj.2022

Chan, T. Y., Wu, C., & Xie, Y. (2011). Measuring the lifetime value of customers acquired from Google search advertising. *Marketing Science*, *30*(5), 837–850. doi:10.1287/mksc.1110.0658

Chandler-Pepelnjak, J. (2008). *Measuring ROI beyond the last ad*. Retrieved from http://advertising.microsoft.com/espana/WWDocs/User/es-es/Advertise/engagement_mapping.pdf

Chang, Y., & Thorson, E. (2004). Television and Web advertising synergies. *Journal of Advertising*, *33*(2), 75–84. doi:10.1080/00913367.2004.10639161

Chatterjee, P., Hoffman, D. L., & Novak, T. P. (2003). Modeling the clickstream: Implications for Web-based advertising efforts. *Marketing Science*, *22*(4), 520–541. doi:10.1287/mksc.22.4.520.24906

Che, H., & Seetharaman, P. B. (2009). "Speed of replacement": Modeling brand loyalty using last-move data. *Journal of Marketing Research*, *46*(4), 494–505. doi:10.1509/jmkr.46.4.494

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, *36*(4), 1–24.

Chen, Y., & Xie, J. (2007). Cross-market network effect with asymmetric customer loyalty: Implications for competitive advantage. *Marketing Science*, *26*(1), 52–66. doi:10.1287/mksc.1060.0238

Chesbrough, H. (2007). Business model innovation: It's not just about technology anymore. *Strategy & Leadership*, *35*(6), 12–17. doi:10.1108/10878570710833714

Chierichetti, F., Kumar, R., Raghavan, P., & Sarlós, T. (2012). Are Web users really Markovian? In A. Mille, F. L. Gandon, J. Misselis, M. Rabinovich, & S. Staab (Eds.), *Proceedings of the 21st International Conference on World Wide Web* (pp. 609–618). ACM.

Cook, S. (2008). The contribution revolution: Letting volunteers build your business. *Harvard Business Review*, *86*(10), 60–69.

Coombes, P. H., & Nicholson, J. D. (2013). Business models and their relationship with marketing: A systematic literature review. *Industrial Marketing Management*, *42*(5), 656–664. doi:10.1016/j.indmarman.2013.05.005

Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). *Introduction to algorithms* (3rd ed.). Cambridge, MA: Massachusetts Institute of Technology.

Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). The consumer decision journey. *McKinsey Quarterly*, *3*, 96–107.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B*, *34*(2), 187–220. Retrieved from http://www.jstor.org/stable/2985181

Craver, T. (2013). *Goodbye, keyword data: Google moves entirely to secure search*. Retrieved from http://searchenginewatch.com/article/2296351/Goodbye-Keyword-Data-Google-Moves-Entirely-to-Secure-Search

Cukier, K. N., & Mayer-Schönberger, V. (2013, April 3). The rise of big data. *Foreign Affairs*. Retrieved from http://www.foreignaffairs.com/articles/139104/kenneth-neil-cukier-and-viktor-mayer-schoenberger/the-rise-of-big-data

Dalessandro, B., Perlich, C., Stitelman, O., & Provost, F. J. (2012). *Causally motivated attribution for online advertising*. New York, NY. Retrieved from http://m6d.com/blog/wp-content/uploads/2012/02/m6d_causal_attribution_2012.pdf

Danaher, P. J., & Dagger, T. S. (2013). Comparing the relative effectiveness of advertising channels: A case study of a multimedia blitz campaign. *Journal of Marketing Research*, *50*(4), 517–534. doi:10.1509/jmr.12.0241

Danaher, P. J., Rust, R. T., Easton, G. S., & Sullivan, M. W. (1996). Indirect financial benefits from service quality. *Quality Management Journal*, *3*(2), 63–75. Retrieved from http://asq.org/data/subscriptions/qmj_open/1996/january/qmjv3i2danaher.pdf

Danneels, E., & Lilien, G. L. (1998). Doctoral programs in business-to-business marketing: Status and prospects. *Journal of Business-to-Business Marketing*, *5*(1-2), 7–34. doi:10.1300/J033v05n01_02

Day, G. S. (2011). Closing the marketing capabilities gap. *Journal of Marketing*, *75*(4), 183–195. doi:10.1509/jmkg.75.4.183

Deighton, J., & Kornfeld, L. (2009). Interactivity's unanticipated consequences for marketers and marketing. *Journal of Interactive Marketing*, *23*(1), 4–10. doi:10.1016/j.intmar.2008.10.001

Dholakia, R. R. & Dholakia, N. (2013). *Scholarly research in marketing: Trends and challenges in the era of big data* (William A. Orme Working Paper Series). Kingston, RI. Retrieved from http://web.uri.edu/business/files/Encycl-Communication-DataMining-n-Marketing-.pdf

Dholakia, U. M., Blazevic, V., Wiertz, C., & Algesheimer, R. (2009). Communal service delivery: How customers benefit from participation in firm-hosted virtual P3 communities. *Journal of Service Research*, *12*(2), 208–226. doi:10.1177/1094670509338618

Dholakia, U. M., Kahn, B. E., Reeves, R., Rindfleisch, A., Stewart, D. W., & Taylor, E. (2010). Consumer behavior in a multichannel, multimedia retailing environment. *Journal of Interactive Marketing*, *24*(2), 86–95. doi:10.1016/j.intmar.2010.02.005

Dijkstra, M., Buijtels, H. E., & Vanraaij, W. (2005). Separate and joint effects of medium type on consumer responses: A comparison of television, print, and the Internet. *Journal of Business Research*, *58*(3), 377–386. doi:10.1016/S0148-2963(03)00105-X

Domingos, P., & Richardson, M. (2001). Mining the network value of customers. In D. Lee, M. Schkolnick, F. J. Provost, & R. Srikant (Eds.), *Proceedings of the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.* ACM.

Dou, W., Lim, K. H., Su, C., Zhou, N., & Cui, N. (2010). Brand positioning strategy using search engine marketing. *MIS Quarterly*, *34*(2), 261–279. Retrieved from http://misq.org/brand-positioning-strategy-using-search-engine-marketing.html

Drèze, X., & Hussherr, F.-X. (2003). Internet advertising: Is anybody watching? *Journal of Interactive Marketing*, *17*(4), 8–23. doi:10.1002/dir.10063

Economist (2010, February 27). The data deluge: Businesses, governments and society are only starting to tap its vast potential. *The Economist*. Retrieved from http://www.economist.com/node/15579717

Econsultancy. (2012a). *Marketing attribution: Valuing the customer journey*. London, UK. Retrieved from http://econsultancy.com/de/reports/marketing-attribution-valuing-the-customer-journey

Econsultancy. (2012b). *Quarterly digital intelligence briefing: Making sense of marketing attribution*. London, UK. Retrieved from https://econsultancy.com/reports/quarterly-digital-intelligence-briefing-making-sense-of-marketing-attribution

Edelman, D. C. (2010). Branding in the digital age. *Harvard Business Review*, *88*(12), 62–69.

Ehret, M., Kashyap, V., & Wirtz, J. (2013). Business models: Impact on business markets and opportunities for marketing research. *Industrial Marketing Management*, *42*(5), 649–655. doi:10.1016/j.indmarman.2013.06.003

Eisenmann, T., Parker, G. G., & van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard Business Review*, *84*(10), 92–101.

Eisenmann, T., Parker, G. G., & van Alstyne, M. W. (2011). Platform envelopment. *Strategic Management Journal*, *32*(12), 1270–1285. doi:10.1002/smj.935

Ellis-Chadwick, F., & Doherty, N. F. (2012). Web advertising: The role of e-mail marketing. *Journal of Business Research*, *65*(6), 843–848. doi:10.1016/j.jbusres.2011.01.005

eMarketer. (2013a). *Advertisers continue rapid adoption of programmatic buying*. Retrieved from http://www.emarketer.com/Article/Advertisers-Continue-Rapid-Adoption-of-Programmatic-Buying/1010414

eMarketer. (2013b). *Worldwide B2C ecommerce: 2013 forecast and comparative estimates*. Retrieved from https://www.emarketer.com/coverage/consumersecommerce

eMarketer. (2014). *Global B2C ecommerce sales to hit $1.5 trillion this year driven by growth in emerging markets*. Retrieved from https://www.emarketer.com/coverage/consumersecommerce

Evans, D. S. (2009). The online advertising industry: Economics, evolution, and privacy. *Journal of Economic Perspectives*, *23*(3), 37–60. doi:10.1257/jep.23.3.37

Farhangi, H. (2010). The path of the smart grid. *IEEE Power & Energy Magazine*, *8*(1), 18–28. doi:10.1109/MPE.2009.934876

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, *27*(8), 861–874. doi:10.1016/j.patrec.2005.10.010

Fischer, M., Albers, S., Wagner, N., & Frie, M. (2011). Dynamic marketing budget allocation across countries, products, and marketing activities. *Marketing Science*, *30*(4), 568–585. doi:10.1287/mksc.1100.0627

Flosi, S., Fulgoni, G. M., & Vollman, A. (2013). If an advertisement runs online and no one sees it, is it still an ad? Empirical generalizations in digital advertising. *Journal of Advertising Research*, *53*(2), 192–199. doi:10.2501/JAR-53-2-192-199

Fulgoni, G. M., & Mörn, M. P. (2009). Whither the click? How online advertising works. *Journal of Advertising Research*, *49*(2), 134–142. doi:10.2501/S0021849909090175

Gelles, D., & Goel, V. (2014, February 19). Facebook enters $16 billion deal for WhatsApp. *The New York Times*. Retrieved from http://dealbook.nytimes.com/2014/02/19/facebook-to-buy-messaging-start-up/?_php=true&_type=blogs&_r=0

Germann, F., Lilien, G. L., & Rangaswamy, A. (2013). Performance implications of deploying marketing analytics. *International Journal of Research in Marketing*, *30*(2), 114–128. doi:10.1016/j.ijresmar.2012.10.001

Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Science*, *55*(10), 1605–1622. doi:10.1287/mnsc.1090.1054

Gneiser, M., Heidemann, J., Klier, M., Landherr, A., & Probst, F. (2012). Valuation of online social networks taking into account users' interconnectedness. *Information Systems and e-Business Management*, *10*(1), 61–84. doi:10.1007/s10257-010-0153-1

Goh, K. Y., Chu, H., & Soh, W. (2009). Mobile advertising: An empirical study of advertising response and search behavior. In J. F. Nunamaker, Jr. & W. L. Currie (Eds.), *Proceedings of the 30th International Conference on Information Systems.*

Goldfarb, A., & Tucker, C. (2011). Online display advertising: Targeting and obtrusiveness. *Marketing Science*, *30*(3), 389–404. doi:10.1287/mksc.1100.0583

Goldfarb, A., & Tucker, C. (2012). Shifts in privacy concerns. *American Economic Review*, *102*(3), 349–353. doi:10.1257/aer.102.3.349

Goldhaber, N. A., & Fitts, G. (1998) U.S. Patent No. 5794210. United States Patent and Trademark Office.

Google Inc. (2014). *About AdWords remarketing lists for search ads*. Retrieved from https://support.google.com/adwords/answer/2701222?hl=en

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, *18*(1), 59–82. doi:10.1177/1525822X05279903

Gulati, R. (2007). Tent poles, tribalism, and boundary spanning: The rigor-relevance debate in management research. *Academy of Management Journal*, *50*(4), 775–782. doi:10.5465/AMJ.2007.26279170

Gupta, S., Hanssens, D. M., Hardie, B. G. S., Kahn, W., Kumar, V., Lin, N.,. . . Sriram, S. (2006). Modeling customer lifetime value. *Journal of Service Research*, *9*(2), 139–155. doi:10.1177/1094670506293810

Gupta, S., & Mela, C. F. (2008). What is a free customer worth? Armchair calculations of nonpaying customers' value can lead to flawed strategies. *Harvard Business Review*, *86*(11), 102–109.

Haan, E. de, Wiesel, T., & Pauwels, K. (2013). *Which advertising forms make a difference in online path to purchase?* (Marketing Science Institute Working Paper Series No. 13). Boston, MA. Retrieved from http://www.msi.org/reports/which-advertising-forms-make-a-difference-in-online-path-to-purchase/

Haenlein, M., & Libai, B. (2013). Targeting revenue leaders for a new product. *Journal of Marketing*, *77*(3), 65–80. doi:10.1509/jm.11.0428

Halbheer, D., Stahl, F., Koenigsberg, O., & Lehmann, D. R. (2014). Choosing a digital content strategy: How much should be free? *International Journal of Research in Marketing*, *31*(2), 192–206. doi:10.1016/j.ijresmar.2013.10.004

Hatch, M. J., & Schultz, M. (2010). Toward a theory of brand co-creation with implications for brand governance. *Journal of Brand Management*, *17*(8), 590–604. doi:10.1057/bm.2010.14

Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science*, *19*(1), 4–21. doi:10.1287/mksc.19.1.4.15178

Hauser, J. R., & Wernerfelt, B. (1990). An evaluation cost model of consideration sets. *Journal of Consumer Research*, *16*(4), 393–408. Retrieved from http://www.jstor.org/stable/2489451

He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, *21*(9), 1263–1284. doi:10.1109/TKDE.2008.239

Helm, S. V. (2003). Calculating the value of customers' referrals. *Managing Service Quality*, *13*(2), 124–133. doi:10.1108/09604520310466815

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52. doi:10.1002/dir.10073

Hennig-Thurau, T., Hofacker, C. F., & Bloching, B. (2013). Marketing the pinball way: Understanding how social media change the generation of value for consumers and companies. *Journal of Interactive Marketing*, *27*(4), 237–241. doi:10.1016/j.intmar.2013.09.005

Hennig-Thurau, T., Malthouse, E. C., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The impact of new media on customer relationships. *Journal of Service Research*, *13*(3), 311–330. doi:10.1177/1094670510375460

Hennig-Thurau, T., & Walsh, G. (2003). Electronic word-of-mouth: Motives for and consequences of reading customer articulations on the Internet. *International Journal of Electronic Commerce*, *8*(2), 51–74. Retrieved from http://www.jstor.org/stable/27751096

Ho, T.-H., Li, S., Park, S.-E., & Shen, Z.-J. M. (2012). Customer influence value and purchase acceleration in new product diffusion. *Marketing Science*, *31*(2), 236–256. doi:10.1287/mksc.1110.0701

Hofacker, C. F. (2012). On research methods in interactive marketing. *Journal of Interactive Marketing*, *26*(1), 1–3. doi:10.1016/j.intmar.2011.10.001

Hogan, J. E., Lemon, K. N., & Libai, B. (2003). What is the true value of a lost customer? *Journal of Service Research*, *5*(3), 196–208. doi:10.1177/1094670502238915

Hogan, J. E., Lemon, K. N., & Libai, B. (2004). Quantifying the ripple: Word-of-mouth and advertising effectiveness. *Journal of Advertising Research*, *44*(3), 271–280. doi:10.1017/S0021849904040243

Hollis, N. (2005). Ten years of learning on how online advertising builds brands. *Journal of Advertising Research*, *45*(2), 255–268. doi:10.1017/S0021849905050270

Homburg, C., Steiner, V. V., & Totzek, D. (2009). Managing dynamics in a customer portfolio. *Journal of Marketing*, *73*(5), 70–89. doi:10.1509/jmkg.73.5.70

Howard, J., & Sheth, J. N. (1969). *A theory of buyer behavior*. New York, NY: John Wiley.

Hoyer, W. D., Chandy, R. K., Dorotic, M., Krafft, M., & Singh, S. S. (2010). Consumer cocreation in new product development. *Journal of Service Research*, *13*(3), 283–296. doi:10.1177/1094670510375604

Hui, S. K., Fader, P. S., & Bradlow, E. T. (2009). Path data in marketing: An integrative framework and prospectus for model building. *Marketing Science*, *28*(2), 320–335. doi:10.1287/mksc.1080.0400

Iyengar, R., Bulte, C. van den, & Valente, T. W. (2011). Opinion leadership and social contagion in new product diffusion. *Marketing Science*, *30*(2), 195–212. doi:10.1287/mksc.1100.0566

Iyer, G., & Padmanabhan, V. (2006). Internet-based service institutions. *Marketing Science*, *25*(6), 598–600. doi:10.1287/mksc.l050.0189

Iyer, G., Soberman, D., & Villas-Boas, J. M. (2005). The targeting of advertising. *Marketing Science*, *24*(3), 461–476. doi:10.1287/mksc.1050.0117

Jaakkola, E., & Alexander, M. (2014). The role of customer engagement behavior in value co-creation: A service system perspective. *Journal of Service Research*, *17*(3), 247–261. doi:10.1177/1094670514529187

Jain, D., & Singh, S. S. (2002). Customer lifetime value research in marketing: A review and future directions. *Journal of Interactive Marketing*, *16*(2), 34–46. doi:10.1002/dir.10032

Janiszewski, C. (1993). Preattentive mere exposure effects. *Journal of Consumer Research*, *20*(3), 376–392. doi:10.1086/209356

Jansen, B. J., Brown, A., & Resnick, M. (2007). Factors relating to the decision to click on a sponsored link. *Decision Support Systems*, *44*(1), 46–59. doi:10.1016/j.dss.2007.02.009

Jansen, B. J., & Schuster, S. (2011). Bidding on the buying funnel for sponsored search and keyword advertising. *Journal of Electronic Commerce Research*, *12*(1), 1–18. Retrieved from http://www.jecr.org/sites/default/files/12_1_p01.pdf

Jansen, B. J., Sobel, K., & Zhang, M. (2011). The brand effect of key phrases and advertisements in sponsored search. *International Journal of Electronic Commerce*, *16*(1), 77–106. doi:10.2753/JEC1086-4415160103

Jaworski, B. J. (2011). On managerial relevance. *Journal of Marketing*, *75*(4), 211–224. doi:10.1509/jmkg.75.4.211

Jiang, Z., & Sarkar, S. (2009). Speed matters: The role of free software offer in software diffusion. *Journal of Management Information Systems*, *26*(3), 207–240. doi:10.2753/MIS0742-1222260307

Jiang, Z. (2010). How to give away software with successive versions. *Decision Support Systems*, *49*(4), 430–441. doi:10.1016/j.dss.2010.05.004

Johnson, M. W., Christensen, C. M., & Kagermann, H. (2008). Reinventing your business model. *Harvard Business Review*, *86*(12), 57–68.

Joo, M., Wilbur, K. C., Cowgill, B., & Zhu, Y. (2014). Television advertising and online search. *Management Science*, *60*(1), 56–73. doi:10.1287/mnsc.2013.1741

Jordan, P., Mahdian, M., Vassilvitskii, S., & Vee, E. (2011). The multiple attribution problem in pay-per-conversion advertising. In W.-Y. Ma, J.-Y. Nie, R. A. Baeza-Yates, T.-S. Chua, & W. B. Croft (Eds.), *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval.* ACM.

Juniper Research. (2014). *Spend on in-app advertising grows to almost 17 billion by 2018*. Retrieved from http://www.juniperresearch.com/viewpressrelease.php?pr=421

Kamins, M. A., Folkes, V. S., & Fedorikhin, A. (2009). Promotional bundles and consumers' price judgments: When the best things in life are not free. *Journal of Consumer Research*, *36*(4), 660–670. doi:10.1086/599806

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, *90*(430), 773–795. doi:10.2307/2291091

Katona, Z., & Sarvary, M. (2008). Network formation and the structure of the commercial World Wide Web. *Marketing Science*, *27*(5), 764–778. doi:10.1287/mksc.1070.0349

Katona, Z., Zubcsek, P. P., & Sarvary, M. (2011). Network effects and personal influences: The diffusion of an online social network. *Journal of Marketing Research*, *48*(3), 425–443. doi:10.1509/jmkr.48.3.425

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, *75*(3), 424–440. Retrieved from http://www.jstor.org/stable/1814809

Kind, H. J., Nilssen, T., & Sørgard, L. (2009). Business models for media firms: Does competition matter for how they raise revenue? *Marketing Science*, *28*(6), 1112–1128. doi:10.1287/mksc.1090.0514

Kireyev, P., Pauwels, K., & Gupta, S. (2013). *Do display ads influence search? Attribution and dynamics in online advertising* (HBS Working Paper No. 13-070). Boston, MA. Retrieved from http://www.hbs.edu/faculty/Publication%20Files/13-070.pdf

Klapdor, S. (2013). *Effectiveness of online marketing campaigns: An investigation into online multichannel and search engine advertising*. Berlin, Germany: Springer/Gabler.

Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. In *Proceedings of the 14th International Joint Conference on Artificial Intelligence* (Vol. 2, pp. 1137–1145). San Francisco, CA: Morgan Kaufmann.

Kozinets, R. V. (2002). The field behind the screen: Using netnography for marketing research in online communities. *Journal of Marketing Research*, *39*(1), 61–72. doi:10.1509/jmkr.39.1.61.18935

Kraemer, T., Hinz, O., & Skiera, B. (2012). Measuring the economic success of marketing investments in two-sided markets. In S. Srinivasan & Kaufmann P. (Eds.), *Proceedings of the 34th ISMS Marketing Science Conference.*

Kumar, V., Aksoy, L., Donkers, B., Venkatesan, R., Wiesel, T., & Tillmanns, S. (2010). Undervalued or overvalued customers: Capturing total customer engagement value. *Journal of Service Research*, *13*(3), 297–310. doi:10.1177/1094670510375602

Kumar, V., Bhaskaran, V., Mirchandani, R., & Shah, M. (2013). Creating a measurable social media marketing strategy: Increasing the value and ROI of intangibles and tangibles for Hokey Pokey. *Marketing Science*, *32*(2), 194–212. doi:10.1287/mksc.1120.0768

Kumar, V., Petersen, J. A., & Leone, R. P. (2007). How valuable is word of mouth? *Harvard Business Review*, *85*(10), 139–146.

Kumar, V., Petersen, J. A., & Leone, R. P. (2010). Driving profitability by encouraging customer referrals: Who, when, and how. *Journal of Marketing*, *74*(5), 1–17. doi:10.1509/jmkg.74.5.1

Kumar, V., Petersen, J. A., & Leone, R. P. (2013). Defining, measuring, and managing business reference value. *Journal of Marketing*, *77*(1), 68–86. doi:10.1509/jm.11.0424

Kumar, V., & Venkatesan, R. (2005). Who are the multichannel shoppers and how do they perform? Correlates of multichannel shopping behavior. *Journal of Interactive Marketing*, *19*(2), 44–62. doi:10.1002/dir.20034

Kuppelwieser, V. G., Simpson, M. C., & Chiummo, G. (2013). 1 + 1 does not always equal value creation: The case of YouTube. *Marketing Letters*, *24*(3), 311–321. doi:10.1007/s11002-013-9246-1

Lamb, C. W., Hair, J. F., & McDaniel, C. (2009). *Essentials of Marketing* (7th ed.). Mason, OH: South-Western Cengage Learning.

Lambrecht, A., & Tucker, C. (2013). When does retargeting work? Information specificity in online advertising. *Journal of Marketing Research*, *50*(5), 561–576. doi:10.1509/jmr.11.0503

Laney, D. (2001). *3D data management: Controlling data volume, velocity, and variety*. Stamford, CT. Retrieved from http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf

Lee, G. (2010). Death of 'last click wins': Media attribution and the expanding use of media data. *Journal of Direct, Data and Digital Marketing Practice*, *12*(1), 16–26. doi:10.1057/dddmp.2010.14

Lee, J., Lee, J., & Feick, L. (2006). Incorporating word-of-mouth effects in estimating customer lifetime value. *Journal of Database Marketing & Customer Strategy Management*, *14*(1), 29–39. doi:10.1057/palgrave.dbm.3250033

Lee, W. M., & Sanderson, M. (2010). Analyzing URL queries. *Journal of the American Society for Information Science and Technology*, *61*(11), 2300–2310. doi:10.1002/asi.21407

Leeflang, P. S. H., Verhoef, P. C., Dahlström, P., & Freundt, T. (2014). Challenges and solutions for marketing in a digital era. *European Management Journal*, *32*(1), 1–12. doi:10.1016/j.emj.2013.12.001

Leeflang, P. S. H., & Wittink, D. R. (2000). Building models for marketing decisions: Past, present and future. *International Journal of Research in Marketing*, *17*(2-3), 105–126. doi:10.1016/S0167-8116(00)00008-2

Lehmann, D. R., McAlister, L., & Staelin, R. (2011). Sophistication in research in marketing. *Journal of Marketing*, *75*(4), 155–165. doi:10.1509/jmkg.75.4.155

Lewis, R. & Nguyen, D. (2014). *A Samsung ad for the iPad? Display advertising's competitive spillovers to search*. Retrieved from http://ssrn.com/abstract=2374414

Lewis, R. A., Rao, J. M., & Reiley, D. H. (2011). Here, there, and everywhere: Correlated online behaviors can lead to overestimates of the effects of advertising. In W.-Y. Ma, J.-Y. Nie, R. A. Baeza-Yates, T.-S. Chua, & W. B. Croft (Eds.), *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval.* ACM.

Li, H. A., & Kannan, P. K. (2014). Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. *Journal of Marketing Research*, *51*(1), 40–56. doi:10.1509/jmr.13.0050

Libai, B., Biyalogorsky, E., & Gerstner, E. (2003). Setting referral fees in affiliate marketing. *Journal of Service Research*, *5*(4), 303–315. doi:10.1177/1094670503251111

Libai, B., Bolton, R. N., Bugel, M. S., Ruyter, K. de, Gotz, O., Risselada, H., & Stephen, A. T. (2010). Customer-to-customer interactions: Broadening the scope of word of mouth research. *Journal of Service Research*, *13*(3), 267–282. doi:10.1177/1094670510375600

Libai, B., Muller, E., & Peres, R. (2013). Decomposing the value of word-of-mouth seeding programs: Acceleration vs. expansion. *Journal of Marketing Research*, *50*(2), 161–176. doi:10.1509/jmr.11.0305

Lilien, G. L. (2011). Bridging the academic – practitioner divide in marketing decision models. *Journal of Marketing*, *75*(4), 196–210. doi:10.1509/jmkg.75.4.196

Lilien, G. L., Roberts, J. H., & Shankar, V. (2013). Effective marketing science applications: Insights from ISMS-MSI Practice Prize finalist papers and projects. *Marketing Science*, *32*(2), 229–245. doi:10.1287/mksc.1120.0756

Lin, C., Venkataram, S., & Jap, S. D. (2013). Media multiplexing behavior: Implications for targeting and media planning. *Marketing Science*, *32*(2), 310–324. doi:10.1287/mksc.1120.0759

Lin, M., Lucas, H. C., & Shmueli, G. (2013). Too big to fail: Large samples and the p-value problem. *Information Systems Research*, *24*(4), 906–917. doi:10.1287/isre.2013.0480

Little, J. D. C. (1970). Models and managers: The concept of a decision calculus. *Management Science*, *16*(8), B-466–B-485. doi:10.1287/mnsc.1040.0267

Little, J. D. C. (1979). Decision support systems for marketing managers. *Journal of Marketing*, *43*(3), 9–26. doi:10.2307/1250143

Little, J. D. C. (2004). Comments on "Models and managers: The concept of a decision calculus". *Management Science*, *50*(12 Supplement), 1854–1860. doi:10.1287/mnsc.1040.0310

Lodish, L. M. (2001). Building marketing models that make money. *Interfaces*, *31*(3), S45. doi:10.1287/inte.31.3s.45.9681

Lohtia, R., Donthu, N., & Yaveroglu, I. (2007). Evaluating the efficiency of Internet banner advertisements. *Journal of Business Research*, *60*(4), 365–370. doi:10.1016/j.jbusres.2006.10.023

Lovett, J. (2009). *A framework for multicampaign attribution measurement*. Cambridge, MA. Retrieved from http://www.forrester.com/A+Framework+For+Multicampaign+Attribution+Measurement/fulltext/-/E-RES48148

Ludwig, S., Ruyter, K. de, Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, *77*(1), 87–103. doi:10.1509/jm.11.0560

Luo, C., Jiang, Z. J., & Yi, C. (2012). Effects of undesired online video advertising choice on user behavior and attitude. In F. G. Joey (Ed.), *Proceedings of the 33rd International Conference on Information Systems.*

Luo, X., Andrews, M., Fang, Z., & Phang, C. W. (2014). Mobile targeting. *Management Science*, *60*(7), 1738–1756. doi:10.1287/mnsc.2013.1836

Lusch, R. F., & Vargo, S. L. (2006). Service-dominant logic: Reactions, reflections and refinements. *Marketing Theory*, *6*(3), 281–288. doi:10.1177/1470593106066781

Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Information Systems Research*, *15*(4), 336–355. doi:10.1287/isre.1040.0032

Malthouse, E. C., Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing customer relationships in the social media era: Introducing the social CRM house. *Journal of Interactive Marketing*, *27*(4), 270–280. doi:10.1016/j.intmar.2013.09.008

Manchanda, P., Dubé, J.-P., Goh, K. Y., & Chintagunta, P. K. (2006). The effect of banner advertising on Internet purchasing. *Journal of Marketing Research*, *43*(1), 98–108. doi:10.1509/jmkr.43.1.98

Manchanda, P., Packard, G. M., & Pattabhiramaiah, A. (2014). *Social dollars: The economic impact of customer participation in a firm-sponsored online community*. Retrieved from http://ssrn.com/abstract=1984350

Marketing Science Institute. (2014). *2014-2016 Research priorities*. Retrieved from http://www.msi.org/research/2014-2016-research-priorities/

McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, *90*(10), 60–68.

McCracken, G. (1998). *The long interview*. *Qualitative Research Methods Series: Vol. 13*. Newbury Park, CA: Sage Publications.

McDonald, E. K., Wilson, H. N., & Konuş, U. (2012). Better customer insight—in real time. *Harvard Business Review*, *90*(9), 102–108.

Moe, W. W., & Fader, P. S. (2004). Capturing evolving visit behavior in clickstream data. *Journal of Interactive Marketing*, *18*(1), 5–19. doi:10.1002/dir.10074

Moe, W. W. (2006). An empirical two-stage choice model with varying decision rules applied to Internet clickstream data. *Journal of Marketing Research*, *43*(4), 680–692. doi:10.1509/jmkr.43.4.680

Montgomery, A. L., Li, S., Srinivasan, K., & Liechty, J. C. (2004). Modeling online browsing and path analysis using clickstream data. *Marketing Science*, *23*(4), 579–595. doi:10.1287/mksc.1040.0073

Morimoto, M., & Chang, S. (2006). Consumers' attitudes toward unsolicited commercial email and postal direct mail marketing methods: Intrusiveness, perceived loss of control, and irritation. *Journal of Interactive Advertising*, *7*(1), 1–11. doi:10.1080/15252019.2006.10722121

Murphy, S. A., & Sen, P. K. (1991). Time-dependent coefficients in a Cox-type regression model. *Stochastic Processes and their Applications*, *39*(1), 153–180. doi:10.1016/0304-4149(91)90039-F

Muthukrishnan, S. (2009). Ad exchanges: Research issues. In S. Leonardi (Ed.): *Vol. 5929. Lecture Notes in Computer Science, Internet and Network Economics* (pp. 1–12). Berlin, Germany: Springer.

Naik, P. A., & Peters, K. (2009). A hierarchical marketing communications model of online and offline media synergies. *Journal of Interactive Marketing*, *23*(4), 288–299. doi:10.1016/j.intmar.2009.07.005

Neslin, S. A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M. L., Thomas, J. S., & Verhoef, P. C. (2006). Challenges and opportunities in multichannel customer management. *Journal of Service Research*, *9*(2), 95–112. doi:10.1177/1094670506293559

Neslin, S. A., & Shankar, V. (2009). Key issues in multichannel customer management: Current knowledge and future directions. *Journal of Interactive Marketing*, *23*(1), 70–81. doi:10.1016/j.intmar.2008.10.005

Neuendorf, K. A. (2002). *The content analysis guidebook*. Thousand Oaks, CA: Sage Publications.

Nikiforakis, N., Kapravelos, A., Joosen, W., Kruegel, C., Piessens, F., & Vigna, G. (2013). Cookieless monster: Exploring the ecosystem of Web-based device fingerprinting. In *Proceedings of the 34th IEEE Symposium on Security and Privacy* (pp. 541–555). IEEE.

Nitzan, I., & Libai, B. (2011). Social effects on customer retention. *Journal of Marketing*, *75*(6), 24–38. doi:10.1509/jm.10.0209

Noe, T., & Parker, G. G. (2005). Winner take all: Competition, strategy, and the structure of returns in the Internet economy. *Journal of Economics & Management Strategy*, *14*(1), 141–164. doi:10.1111/j.1430-9134.2005.00037.x

Nottorf, F. (2014). Modeling the clickstream across multiple online advertising channels using a binary logit with Bayesian mixture of normals. *Electronic Commerce Research and Applications*, *13*(1), 45–55. doi:10.1016/j.elerap.2013.07.004

Oestreicher-Singer, G., & Zalmanson, L. (2013). Content or community?: A digital business strategy for content providers in the social age. *MIS Quarterly*, *37*(2), 591–616. Retrieved from http://misq.org/content-or-community-a-digital-business-strategy-for-content-providers-in-the-social-age.html?SID=r1mha6nh5pjii8hji4lfbfe5d1

Osterwalder, A., Pigneur, Y., & Tucci, C. L. (2005). Clarifying business models: origins, present, and future of the concept. *Communications of the Association for Information Systems*, *16*. Retrieved from http://aisel.aisnet.org/cais/vol16/iss1/1

Osterwalder, A., & Pigneur, Y. (2010). *Business model generation*. Hoboken, NJ: Wiley & Sons.

Osur, A. (2012). *The Forrester Wave: Interactive attribution vendors, Q2 2012*. Cambridge, MA. Retrieved from http://www.forrester.com/The+Forrester+Wave+Interactive+Attribution+Vendors+Q2+2012/fulltext/-/E-RES72681

Pancras, J., & Sudhir, K. (2007). Optimal marketing strategies for a customer data intermediary. *Journal of Marketing Research*, *44*(4), 560–578. doi:10.1509/jmkr.44.4.560

Papadimitriou, P., Krishnamurthy, P., Lewis, R. A., Reiley, D. H., & Garcia-Molina, H. (2011). Display advertising impact: Search lift and social influence. In W.-Y. Ma, J.-Y. Nie, R. A. Baeza-Yates, T.-S. Chua, & W. B. Croft (Eds.), *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval.* ACM.

Papatla, P., & Bhatnagar, A. (2002). Choosing the right mix of on-line affiliates: How do you select the best? *Journal of Advertising*, *31*(3), 69–81. doi:10.1080/00913367.2002.10673677

Papies, D., Eggers, F., & Wlömert, N. (2011). Music for free?: How free ad-funded downloads affect consumer choice. *Journal of the Academy of Marketing Science*, *39*(5), 777–794. doi:10.1007/s11747-010-0230-5

Parent, M., Plangger, K., & Bal, A. (2011). The new WTP: Willingness to participate. *Business Horizons*, *54*(3), 219–229. doi:10.1016/j.bushor.2011.01.003

Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. *Journal of Management Information Systems*, *27*(2), 159–188. doi:10.2753/MIS0742-1222270205

Pauwels, K., & Weiss, A. (2008). Moving from free to fee: How online firms market to change their business model successfully. *Journal of Marketing*, *72*(3), 14–31. doi:10.1509/jmkg.72.3.14

Pavlou, P. A., & Stewart, D. W. (2000). Measuring the effects and effectiveness of interactive advertising: A research agenda. *Journal of Interactive Advertising*, *1*(1), 62–78. Retrieved from http://jiad.org/article6.html

Payne, A. F., Storbacka, K., & Frow, P. (2008). Managing the co-creation of value. *Journal of the Academy of Marketing Science*, *36*(1), 83–96. doi:10.1007/s11747-007-0070-0

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. doi:10.1037//0278-7393.14.3.534

Perreault, W. D., & Leigh, L. E. (1989). Reliability of nominal data based on qualitative judgments. *Journal of Marketing Research*, *26*(2), 135–148. doi:10.2307/3172601

Pfeifer, P. E., & Carraway, R. L. (2000). Modeling customer relationships as Markov chains. *Journal of Interactive Marketing*, *14*(2), 43–55. doi:10.1002/(SICI)1520-6653(200021)14:2<43::AID-DIR4>3.0.CO;2-H

Poel, D. van den, & Buckinx, W. (2005). Predicting online-purchasing behaviour. *European Journal of Operational Research*, *166*(2), 557–575. doi:10.1016/j.ejor.2004.04.022

Prasad, A., Mahajan, V., & Bronnenberg, B. J. (2003). Advertising versus pay-per-view in electronic media. *International Journal of Research in Marketing*, *20*(1), 13–30. doi:10.1016/S0167-8116(02)00119-2

PriceWaterhouseCoopers. (2014). *IAB Internet advertising revenue report 2013*. Retrieved from http://www.iab.net/media/file/IAB_Internet_Advertising_Revenue_Report_FY_2013.pdf

Provost, F. J., Fawcett, T., & Kohavi, R. (1998). The case against accuracy estimation for comparing induction algorithms. In J. W. Shavlik (Ed.), *Proceedings of the 15th International Conference on Machine Learning* (pp. 445–453). Morgan Kaufmann.

Raman, K., Mantrala, M. K., Sridhar, S., & Tang, Y. (2012). Optimal resource allocation with time-varying marketing effectiveness, margins and costs. *Journal of Interactive Marketing*, *26*(1), 43–52. doi:10.1016/j.intmar.2011.05.001

Ramsey, G. (2009). *Online brand measurement: Connecting the dots*. New York, NY. Retrieved from http://www.emarketer.com/Article/Taking-Measure-of-Brand-Measurement/1007162

Ransbotham, S., Kane, G. C., & Lurie, N. H. (2012). Network characteristics and the value of collaborative user-generated content. *Marketing Science*, *31*(3), 387–405. doi:10.1287/mksc.1110.0684

Reibstein, D. J., Day, G. S., & Wind, J. (2009). Guest editorial: Is marketing academia losing its way? *Journal of Marketing*, *73*(4), 1–3. doi:10.1509/jmkg.73.4.1

Riley, E. (2009). *The Forrester Wave: Interactive attribution, Q4 2009*. Cambridge, MA. Retrieved from http://www.forrester.com/The+Forrester+Wave+Interactive+Attribution+Q4+2009/fulltext/-/E-RES55372

Roberts, J. H., Kayande, U., & Stremersch, S. (2014). From academic research to marketing practice: Some further thoughts. *International Journal of Research in Marketing*, *31*(2), 144–146. doi:10.1016/j.ijresmar.2013.12.001

Roberts, J. H., & Lattin, J. M. (1997). Consideration: Review of research and prospects for future insights. *Journal of Marketing Research*, *34*(3), 406–410. Retrieved from http://www.jstor.org/stable/3151902

Rochet, J.-C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990–1029. doi:10.1162/154247603322493212

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: A progress report. *Rand Journal of Economics*, *37*(3), 645–667. doi:10.1111/j.1756-2171.2006.tb00036.x

Rose, D. E., & Levinson, D. (2004). Understanding user goals in Web search. In S. I. Feldman, M. Uretsky, M. Najork, & C. E. Wills (Eds.), *Proceedings of the 13th International Conference on World Wide Web* (pp. 13–19). ACM.

Rust, R. T., Ambler, T., Carpenter, G. S., Kumar, V., & Srivastava, R. K. (2004). Measuring marketing productivity: Current knowledge and future directions. *Journal of Marketing*, *68*(4), 76–89. doi:10.1509/jmkg.68.4.76.42721

Rust, R. T., & Cooil, B. (1994). Reliability measures for qualitative data: Theory and implications. *Journal of Marketing Research*, *31*(1), 1–14. doi:10.2307/3151942

Rust, R. T., & Kannan, P. K. (2003). E-service: A new paradigm for business in the electronic environment. *Communications of the ACM*, *46*(6), 36–42. doi:10.1145/777313.777336

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of Marketing*, *68*(1), 109–127. doi:10.1509/jmkg.68.1.109.24030

Rust, R. T., Zahorik, A. J., & Keiningham, T. L. (1995). Return on quality (ROQ): Making service quality financially accountable. *Journal of Marketing*, *59*(2), 58–70. doi:10.2307/1252073

Rust, R. T. (2006). From the editor: The maturation of marketing as an academic discipline. *Journal of Marketing*, *70*(3), 1–2. doi:10.1509/jmkg.70.3.1

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research*, *48*(1), 87–102. doi:10.1509/jmkr.48.1.87

Rutz, O. J., Trusov, M., & Bucklin, R. E. (2011). Modeling indirect effects of paid search advertising: Which keywords lead to more future visits? *Marketing Science*, *30*(4), 646–665. doi:10.1287/mksc.1110.0635

Ryals, L. (2002). Are your customers worth more than money? *Journal of Retailing and Consumer Services*, *9*(5), 241–251. doi:10.1016/S0969-6989(02)00005-X

Ryals, L. (2008). Determining the indirect value of a customer. *Journal of Marketing Management*, *24*(7-8), 847–864. doi:10.1362/026725708X345542

Schmitt, P., Skiera, B., & Bulte, C. van den. (2011). Referral programs and customer value. *Journal of Marketing*, *75*(1), 46–59. doi:10.1509/jmkg.75.1.46

Schumann, J. H., Wangenheim, F. von, & Gröne, N. (2014). Targeted online advertising: Using reciprocity appeals to increase acceptance among users of free Web services. *Journal of Marketing*, *78*(1), 59–75. doi:10.1509/jm.11.0316

Schwarz, G. E. (1978). Estimating the dimension of a model. *Annals of Statistics*, *6*(2), 461–464. doi:10.1214/aos/1176344136

Shankar, V., & Malthouse, E. C. (2007). The growth of interactions and dialogs in interactive marketing. *Journal of Interactive Marketing*, *21*(2), 2–4. doi:10.1002/dir.20080

Shankar, V., Venkatesh, A., Hofacker, C. F., & Naik, P. A. (2010). Mobile marketing in the retailing environment: Current insights and future research avenues. *Journal of Interactive Marketing*, *24*(2), 111–120. doi:10.1016/j.intmar.2010.02.006

Shao, X., & Li, L. (2011). Data-driven multi-touch attribution models. In C. Apté, J. Ghosh, & P. Smyth (Eds.), *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 258–264). ACM.

Shapiro, C., & Varian, H. R. (1998). *Information rules: A strategic guide to the network economy*. Boston, MA: Harvard Business Press.

Shapiro, S., MacInnis, D. J., & Heckler, S. E. (1997). The effects of incidental ad exposure on the formation of consideration sets. *Journal of Consumer Research*, *24*(1), 94–104. doi:10.1086/209496

Shocker, A. D., Ben-Akiva, M., Boccara, B., & Nedungadi, P. (1991). Consideration set influences on consumer decision-making and choice: Issues, models, and suggestions. *Marketing Letters*, *2*(3), 181–197. doi:10.1007/BF00554125

Siegele, L. (2014, January 18). A Cambrian moment. *The Economist*. Retrieved from http://www.economist.com/node/21593580/print

Sinha, P., & Zoltners, A. A. (2001). Sales-force decision models: Insights from 25 years of implementation. *Interfaces*, *31*(3), S8. doi:10.1287/inte.31.4.8.9675

Sood, A., James, G. M., & Tellis, G. J. (2009). Functional regression: A new model for predicting market penetration of new products. *Marketing Science*, *28*(1), 36–51. doi:10.1287/mksc.1080.0382

Spiggle, S., & Sewall, M. A. (1987). A choice sets model of retail selection. *Journal of Marketing*, *51*(2), 97–111. doi:10.2307/1251132

Sriram, S., Manchanda, P., Bravo, M. E., Chu, J., Ma, L., Song, M.,. . . Subramanian, U. (2014). Platforms: A multiplicity of research opportunities. *Marketing Letters*, *forthcoming.* doi:10.1007/s11002-014-9314-1

Stahl, H. K., Matzler, K., & Hinterhuber, H. H. (2003). Linking customer lifetime value with shareholder value. *Industrial Marketing Management*, *32*(4), 267–279. doi:10.1016/S0019-8501(02)00188-8

Stephen, A. T., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a microlending marketplace. *Journal of Marketing Research*, *49*(5), 624–639. doi:10.1509/jmr.09.0401

Stephen, A. T., & Toubia, O. (2010). Deriving value from social commerce networks. *Journal of Marketing Research*, *47*(2), 215–228. doi:10.1509/jmkr.47.2.215

Strauss, A. L., & Corbin, J. (1990). *Basics of qualitative research: Grounded theory procedures and techniques*. Newbury Park, CA: Sage Publications.

Stremersch, S., Tellis, G. J., Franses, P. H., & Binken, J. L. (2007). Indirect network effects in new product growth. *Journal of Marketing*, *71*(3), 52–74. doi:10.1509/jmkg.71.3.52

Styan, G. P. H., & Smith, H. (1964). Markov chains applied to marketing. *Journal of Marketing Research*, *1*(1), 50–55. doi:10.2307/3150320

Tabachnick, B., & Fidell, L. S. (2012). *Using multivariate statistics* (6th ed.). Boston, MA: Pearson.

Teece, D. J. (2010). Business models, business strategy and innovation. *Long Range Planning*, *43*(2), 172–194. doi:10.1016/j.lrp.2009.07.003

Teradata Corporation. (2013). *Data-driven: How marketers profit from technology in a multi-channel world*. London, UK. Retrieved from http://www.ecircle.com/fileadmin/files/pdfs/04_Resource_Centre/4.4._Studien/UK/Teradata-eCircle_Data-Driven-Marketing-Survey-2013_UK.pdf

Terlutter, R., & Capella, M. L. (2013). The gamification of advertising: Analysis and research directions of in-game advertising, advergames, and advertising in social network games. *Journal of Advertising*, *42*(2-3), 95–112. doi:10.1080/00913367.2013.774610

Tezinde, T., Smith, B., & Murphy, J. (2002). Getting permission: Exploring factors affecting permission marketing. *Journal of Interactive Marketing*, *16*(4), 28–36. doi:10.1002/dir.10041

The CMO Club & Visual IQ, Inc. (2014). *Big data, attribution & omni-channel*. Retrieved from http://www.visualiq.com/sites/default/files/PDF-download-graphics/study_building_bridges_to_the_promised_land.pdf

Tian, L., Zucker, D., & Wei, L. J. (2005). On the Cox model with time-varying regression coefficients. *Journal of the American Statistical Association*, *100*(469), 172–183. doi:10.1198/016214504000000845

Trusov, M., Bodapati, A. V., & Bucklin, R. E. (2010). Determining influential users in Internet social networks. *Journal of Marketing Research*, *47*(4), 643–658. doi:10.1509/jmkr.47.4.643

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an Internet social networking site. *Journal of Marketing*, *73*(5), 90–102. doi:10.1509/jmkg.73.5.90

Tucker, C., & Zhang, J. (2010). Growing two-sided networks by advertising the user base: A field experiment. *Marketing Science*, *29*(5), 805–814. doi:10.1287/mksc.1100.0560

Tucker, C. (2012). The implications of improved attribution and measurability for online advertising markets. In *Competition in the Online Environment.* Retrieved from https://www.ipria.org/events/conf/Competition_Conference/Measureabiltiy_and_online_ads.pdf

Turn Inc. (2013). *Global Digital Audience Report: July to September 2013*. Redwood City, CA. Retrieved from http://www.turn.com/proof#digitalaudiencereport

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. doi:10.1126/science.185.4157.1124

Vakratsas, D., & Ambler, T. (1999). How advertising works: What do we really know? *Journal of Marketing*, *63*(1), 26–43. doi:10.2307/1251999

van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behavior: Theoretical foundations and research directions. *Journal of Service Research*, *13*(3), 253–266. doi:10.1177/1094670510375599 van Eimeren, B., & Frees, B. (2013). Rasanter Anstieg des Internetkonsums – Onliner fast drei Stunden täglich im Netz. *Media Perspektiven*, (7-8), 358–372. Retrieved from http://www.media-perspektiven.de/uploads/tx_mppublications/0708-2013_Eimeren_Frees_01.pdf

Varadarajan, R., & Yadav, M. S. (2009). Marketing strategy in an Internet-enabled environment: A retrospective on the first ten years of JIM and a prospective on the next ten years. *Journal of Interactive Marketing*, *23*(1), 11–22. doi:10.1016/j.intmar.2008.10.002

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. *Journal of the Academy of Marketing Science*, *36*(1), 1–10. doi:10.1007/s11747-007-0069-6

Vega, T. (2013, April 8). Sponsoring articles, not just ads. *The New York Times*, pp. B1. Retrieved from http://www.nytimes.com/2013/04/08/business/media/sponsors-now-pay-for-online-articles-not-just-ads.html?pagewanted=all&_r=1&

Verhoef, P. C., Neslin, S. A., & Vroomen, B. (2007). Multichannel customer management: Understanding the research-shopper phenomenon. *International Journal of Research in Marketing*, *24*(2), 129–148. doi:10.1016/j.ijresmar.2006.11.002

Verhoef, P. C., Venkatesan, R., McAlister, L., Malthouse, E. C., Krafft, M., & Ganesan, S. (2010). CRM in data-rich multichannel retailing environments: A review and future research directions. *Journal of Interactive Marketing*, *24*(2), 121–137. doi:10.1016/j.intmar.2010.02.009

Verleye, K., Gemmel, P., & Rangarajan, D. (2014). Managing engagement behaviors in a network of customers and stakeholders: Evidence from the nursing home sector. *Journal of Service Research*, *17*(1), 68–84. doi:10.1177/1094670513494015

Villanueva, J., Yoo, S., & Hanssens, D. M. (2008). The impact of marketing-induced versus word-of-mouth customer acquisition on customer equity growth. *Journal of Marketing Research*, *45*(1), 48–59. doi:10.1509/jmkr.45.1.48

Vock, M., Dolen, W. van, & Ruyter, K. de (2013). Understanding willingness to pay for social network sites. *Journal of Service Research*, *16*(3), 311–325. doi:10.1177/1094670512472729

Volinsky, C. T., & Raftery, A. E. (2000). Bayesian information criterion for censored survival models. *Biometrics*, *56*(1), 256–262. doi:10.1111/j.0006-341X.2000.00256.x

Voorveld, H. A., Neijens, P. C., & Smit, E. G. (2011). Opening the black box: Understanding cross-media effects. *Journal of Marketing Communications*, *17*(2), 69–85. doi:10.1080/13527260903160460

Wangenheim, F. von, & Bayón, T. (2007). The chain from customer satisfaction via word-of-mouth referrals to new customer acquisition. *Journal of the Academy of Marketing Science*, *35*(2), 233–249. doi:10.1007/s11747-007-0037-1

Wasserman, L. (2000). Bayesian model selection and model averaging. *Journal of Mathematical Psychology*, *44*(1), 92–107. doi:10.1006/jmps.1999.1278

Weinberg, B. D., & Berger, P. D. (2011). Connected customer lifetime value: The impact of social media. *Journal of Direct, Data and Digital Marketing Practice*, *12*(4), 328–344. doi:10.1057/dddmp.2011.2

Westbrook, R. A. (1987). Product/consumption-based affective responses and post-purchase processes. *Journal of Marketing Research*, *24*(3), 258–270. doi:10.2307/3151636

Wiesel, T., Pauwels, K., & Arts, J. (2011). Marketing's profit impact: Quantifying online and off-line funnel progression. *Marketing Science*, *30*(4), 604–611. doi:10.1287/mksc.1100.0612

Winterberry Group. (2013). *Programmatic everywhere ? Data, technology and the future of audience engagement*. Retrieved from http://www.iab.net/media/file/WinterberryGroupWhitePaperProgrammaticEverywhere.pdf

Wu, J., & Rangaswamy, A. (2003). A fuzzy set model of search and consideration with an application to an online market. *Marketing Science*, *22*(3), 411–434. doi:10.1287/mksc.22.3.411.17738

Wübben, M., & Wangenheim, F. von (2008). Instant customer base analysis: Managerial heuristics often “get it right”. *Journal of Marketing*, *72*(3), 82–93. doi:10.1509/jmkg.72.3.82

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: use, characteristics, and impact. *MIS Quarterly*, *31*(1), 137–209. Retrieved from http://www.misq.org/e-commerce-product-recommendation-agents-use-characteristics-and-impact.html

Xu, L., Duan, J. A., & Whinston, A. B. (2014). Path to purchase: A mutually exciting point process model for online advertising and conversion. *Management Science*, *60*(6), 1392–1412. doi:10.1287/mnsc.2014.1952

Yadav, M. S., & Pavlou, P. A. (2014). Marketing in computer-mediated environments: Research synthesis and new directions. *Journal of Marketing*, *78*(1), 20–40. doi:10.1509/jm.12.0020

Yang, S., & Ghose, A. (2010). Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence? *Marketing Science*, *29*(4), 602–623. doi:10.1287/mksc.1090.0552

Zeithaml, V. A. (2000). Service quality, profitability, and the economic worth of customers: What we know and what we need to learn. *Journal of the Academy of Marketing Science*, *28*(1), 67–85. doi:10.1177/0092070300281007

Zhang, J., Farris, P. W., Irvin, J. W., Kushwaha, T., Steenburgh, T. J., & Weitz, B. A. (2010). Crafting integrated multichannel retailing strategies. *Journal of Interactive Marketing*, *24*(2), 168–180. doi:10.1016/j.intmar.2010.02.002

Zhang, K., Evgeniou, T., Padmanabhan, V., & Richard, E. (2012). Content contributor management and network effects in a UGC environment. *Marketing Science*, *31*(3), 433–447. doi:10.1287/mksc.1110.0639

Zhu, J., & Tan, B. C. Y. (2007). Effectiveness of blog advertising: Impact of communicator expertise, advertising intent, and product involvement. In S. Rivard & J. Webster (Eds.), *Proceedings of the 28th International Conference on Information Systems* (p. 121).

Zott, C., Amit, R., & Massa, L. (2011). The business model: Recent developments and future research. *Journal of Management*, *37*(4), 1019–1042. doi:10.1177/0149206311406265