

CRM in Data-Rich Multichannel Retailing Environments: A Review and Future Research Directions[☆]

Peter C. Verhoef,^{a,*} Rajkumar Venkatesan,^b Leigh McAlister,^c Edward C. Malthouse,^d
Manfred Krafft^e & Shankar Ganesan^f

^a University of Groningen, Faculty of Economics and Business, Department of Marketing, Office WSN 331, P.O. Box 800, 9700 AV Groningen, The Netherlands

^b Darden School of Business, University of Virginia, USA

^c McCombs School of Business, University of Texas, Austin, USA

^d Medill School of Journalism, Northwestern University, USA

^e Institute of Marketing, University of Munster, Germany

^f Eller College of Management, University of Arizona

Abstract

Many retailers have collected large amounts of customer data using, for example, loyalty programs. We provide an overview of the extant literature on customer relationship management (CRM), with a specific focus on retailing. We discuss how retailers can gather customer data and how they can analyze these data to gain useful customer insights. We provide an overview of the methods predicting customer responses and behavior over time. We also discuss the existing knowledge on the application of marketing actions in a CRM context, while providing an in-depth discussion on CRM and firm value. We outline future research directions based on the literature review and retail practice insights.

© 2009 Direct Marketing Educational Foundation, Inc. Published by Elsevier Inc. All rights reserved.

Keywords: Customer relationship management; Database; Multichannel marketing; Retailing

Introduction

Over the past decade, retailers have been able to collect enormous amounts of information at the customer level measuring customer purchases, marketing activities, and customer attitudes. An important example is Tesco, which is using its Loyalty Card as a core element of its marketing strategy (e.g., Humby and Hunt 2003). Despite this trend, many retailers have also decided not to invest in building large customer databases. One reason is to be able to focus on low prices and operational excellence as exemplified by discount retailers such as Aldi, Lidl, and Wal-Mart. While these retailers still collect large amounts of data, it is often not at the customer

level. The ubiquity of retail data, regardless of whether at the customer level or not, has created tremendous opportunities as well as challenges for both retail practitioners and researchers in retailing.

On the practitioner side, the results of using customer data are mixed. Tesco is one of the successful retailers that extensively use a customer database and is frequently cited as a successful benchmark in textbooks and the business press (Humby and Hunt 2003; Kumar and Reinartz 2005). However, other retailers have not been successful at leveraging their customer databases. A McKinsey study reports that the majority of retailers are unable to recover the investments in loyalty programs, especially because only less than 50% of customers increase their spending after enrolling in a loyalty program (Cigliano et al. 2000).

The practitioner dilemma has been reflected in multiple discussions that have arisen within the academic community on the effectiveness of loyalty programs in retailing (e.g., Dowling and Uncles 1997; Shugan 2005). Numerous empirical studies that use large customer databases examine how firms can

[☆] We thank all participants of the Thought Leader conference on Topics Multichannel in Retailing for their useful comment during this inspiring conference. We specifically thank the editor Venky Shankar and two anonymous reviewers for providing useful feedback.

* Corresponding author.

E-mail address: p.c.verhoef@rug.nl (P.C. Verhoef).

increase loyalty metrics such as retention rates, cross-buying and customer share (e.g., Verhoef 2003; Verhoef, Frances, and Hoekstra 2001; Kumar, Venkatesan, and Reinartz 2008), and/or how firms can predict these metrics (e.g., Fader, Hardie, and Lee 2005; Neslin et al. 2006a). Other studies have specifically focused on how firms can influence and optimize customer value (e.g., Rust and Verhoef 2005; Venkatesan and Kumar 2004; Venkatesan, Kumar, and Bohling 2007). In sum, there is an existing knowledge base on how to influence and predict customer loyalty and how to optimize customer value (for overviews, see Gupta and Zeithaml 2006; Verhoef, van Doorn, and Dorotic 2007; Blattberg, Malthouse, and Neslin 2009).

In addition to customer value management, multichannel retailing has gained importance as a consequence of the ability of the retailers to amass large customer databases and more broadly ability to obtain a view of the customers across several channels. Multichannel retailing presents the retailer with the opportunity to improve customer profitability by offering a variety of transaction options for the customer. At the same time, the increasing multichannel orientation of retailing practice has created huge challenges for retailers in having real-time access to reliable data across different channels and in understanding and predicting customer behavior across different channels (e.g., Ansari, Mela, and Neslin 2008; Arian 2008; Dholakia et al. 2010; Kushwaha and Shankar 2007; Neslin et al. 2006b; Neslin and Shankar 2009; Verhoef, Neslin, and Vroomen 2007; Venkatesan, Kumar and Ravishanker 2007). For example, several stores such as Best Buy offer customers the option of ordering products online and picking up the products in a nearby offline store. The A CNET.com research shows that execution of this option still remains a challenge for several retailers¹. Specifically, the ability to immediately recognize a customer's online order in the offline store still remains a challenge for retailers.

While there is research in marketing that has looked at the impact of various aspects of the customer relationship management (CRM) process on customer outcomes (Reinartz and Kumar 2003; Du, Kamakura, and Mela 2007), many retailers do not collect the right data, analyze the data appropriately, or initiate the optimal marketing actions to achieve the best customer outcomes, possibly leading to many failed CRM implementations. In this paper, we discuss the application of CRM in retail environments. We elaborate on current knowledge from the academic marketing literature and discuss its relevance in the increasingly multichannel and multimedia retail environment. Furthermore, we provide new research directions on CRM in data-rich retail environments.

The remainder of this paper is structured as follows. We first discuss the conceptual role of CRM in retail environments and present our conceptual model. Subsequently, we address the specific topics within the conceptual model, such as data usage and the application of marketing actions. We address specific research questions within each topic. We also provide a

discussion of future research opportunities within each topic covered by our conceptual model.

CRM in retailing

For the purpose of this article, we define CRM as the practice of analyzing and utilizing marketing databases and leveraging communication technologies to determine corporate practices and methods that will maximize the lifetime value of each individual customer (Kumar and Reinartz 2005, p. 5; also see Reinartz, Krafft, and Hoyer 2004 for an overview). Fig. 1 outlines how CRM can be used in retailing. Marketing management teaches the retailer to target a specific market segment having similar wants and needs, understand this segment, create a brand concept that will be meaningful to this segment, and use the concept to engineer a unique *shopping experience* for each segment (Grewal, Levy, and Kumar 2009; Verhoef et al. 2009). The collective set of interactions between the retailer and the firm communicates the brand concept to shoppers, thereby associating it with the store. This process is illustrated in the left-most part of Fig. 1 (Calder and Malthouse 2005). For example, some retailers that have highly differentiated experiences include Aldi, Ikea, Trader Joe, Whole Foods, and Nordstrom. As another example, Gallery Furniture has a brand concept focused on being a straight shooter who offers high-quality furniture at a fair price and guarantees delivery on the same day as the purchase.

CRM enables the firm to take this process further by identifying smaller groups of customers with homogeneous needs, which are sometimes called *customer segments* or *sub-segments* (Batra 1999; Humby and Hunt 2003; Malthouse 2003; Reutterer et al. 2006; Malthouse and Calder 2006). As illustrated in the middle part of Fig. 1, once sub-segments of customers have been identified, the retailer can understand their needs and then create customized contacts – including offers – that will more closely meet the needs of each subgroup. An issue that sometimes arises when creating such contacts is that they should be consistent with the overarching brand concept; a retailer that fails to do this will confuse its customers over the meaning of the brand.

The right side of the figure above shows that the process of sub-segmenting customers can be extended to individual customers, or *segments of one*. Peppers and Rogers (1997) call this one-to-one marketing. Based on the analysis of individual customer data, retailers create customized offers for individual customers (Ansari and Mela 2003; Montgomery and Smith 2009). An additional step is that CRM-interventions are planned in such a way that the profitability/lifetime value



Fig. 1. Business models around customers in retailing.

¹ "Instore Pickup needs to work every time. It Doesn't." Don Resinger, CNET.com, March 2009.

of each customer is optimized (Rust and Verhoef 2005; Kumar et al. 2009).

Conceptual model

As previously described, the main goal of this article is to discuss notable ways in which retailers are leveraging data from customer relationships to improve performance outcomes related to revenues, market share, innovation, customer value, and long-term competitive advantage. To highlight these issues, Fig. 2 offers a broad-based conceptual model.

The starting point of this conceptual model is the explicit recognition that the current retail environment is characterized by overwhelming amounts of data at both individual customer level and at the aggregate store level (Blattberg, Glazer, and Little 1994; Bucklin and Gupta 2002). In addition, upstream suppliers may provide significant amounts of data that can be utilized by the retailer to create superior customer value (Ganesan et al. 2009; Smit 2006). Given the diversity of data sources, data integration is a key challenge for the retailer.

Once data is collected and integrated, the next step is to derive managerial insights to make better decisions and improve performance (Davenport and Harris 2007; Jayachandran et al. 2005). As discussed in the section below on data usage, CRM decisions are primarily concerned about creating relevant contacts, selecting appropriate customers to receive contacts, delivering the contacts at the right time, estimating the value of customers and identifying best customers. Typically, both descriptive and predictive models are used to understand the data; however, it is imperative that the application of various models is driven by a careful examination and understanding of the retailer’s business model. Finally, retailers need to assess the impact of their marketing actions by measuring specific outcomes, such as customer share and customer lifetime value (Petersen et al. 2009). These customer level outcomes are assumed to eventually affect firm value (e.g., Gupta, Lehmann and Stuart 2005). The so far described process model focuses on the process from data to performance outcomes. The issue of CRM implementation within retail firms arises before the data collection and resource allocation and can affect the whole retail CRM process (Reinartz, Krafft, and Hoyer 2004). We will therefore also include this as a separate part in our conceptual model that covers and affects the whole CRM process in retailing.

Table 1 gives an overview of studies per topic in our conceptual model and the most important findings of these studies. The next sections will examine each of these sections in more detail, where we first discuss the existing literature and provide important future research directions in each of these areas.

CRM data in retailing

Retailers often record transaction data, which can be aggregated to the customer level measuring the number of previous transactions, historical value, and types of products purchased (Verhoef et al. 2003). It can also be aggregated to store level, producing metrics such as total number of visits to a store, total store sales, and category sales (Bucklin and Gupta 2002). The main focus of this paper is on individual customer data. Major issues confronted regarding data collection include: consumer privacy, sales force empowerment, and data quality and reliability.

Consumer privacy

Individual data are collected in different ways depending on the type of retailer. The direct nature of the business models of cataloguers and online retailers allow them to associate transactions with customers in their databases. Store- or bricks-and-mortar retailers, in contrast, frequently face difficulties linking transactions to individual customers unless they have a loyalty program. For example, it is usually not practical to gather information identifying a customer who makes a cash purchase. Several issues then become prevalent. First, are customers willing to provide the data? A few studies in the direct marketing and public policy literature have investigated privacy issues (e.g., see Peltier, Milne, and Phelps 2009). One general finding is that only a limited percentage of customers – privacy activists – tend to worry about their privacy (e.g., Fletcher 2003; Ackerman, Cranor, and Reagle 1999). Milne and Boza (2000) report that these privacy concerns are mainly present in financial services and telecommunications, while they are less present for supermarkets. Despite the existence of privacy concerns, their effect on the provision of data (e.g., participating in loyalty programs) is not strong (van Doorn, Verhoef, and Bijmolt 2007).

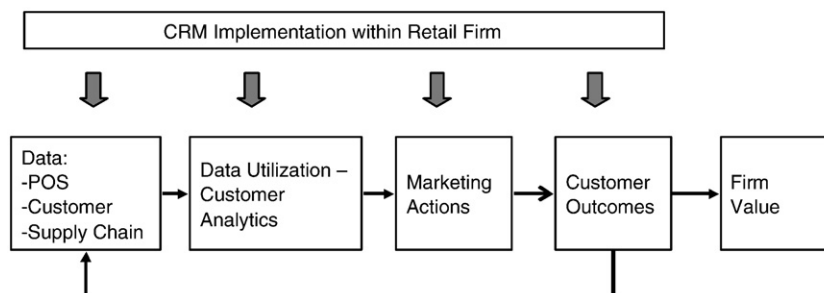


Fig. 2. Conceptual model.

Table 1
A summary of relevant CRM literature.

Topic	Exemplary studies	Key findings
<i>Data</i>		
▪ Customer data provision	Fletcher (2003); Milne and Boza (2000); van Doorn, Verhoef, and Bijmolt (2007)	Only a small segment of customers, especially for supermarkets, have privacy concerns. Participation in loyalty programs is not affected by consumers' privacy concerns.
▪ Sales rep's data provision	Ahearn, Rapp, and Schillewaert (2007)	Usage of CRM technology can improve sales person's targeting abilities, presentation skills and productivity.
▪ Data quality and integration	Neslin et al. (2006b); Verhoef et al. (2003); Zahay and Griffin (2002)	Data quality is positively related to firm performance. However, marginal benefits of improved quality will decrease with increased cost. The click-stream provides online retailers with improved opportunities for collecting quality data.
▪ Online data	Arikan (2008); Bucklin and Sismeiro (2009); Moe and Fader (2004),	
<i>Data utilization-analytics</i>		
▪ Making the right offer	Bodapati (2008); Montgomery and Smith (2009); Malthouse and Calder (2006)	Personalization of offers such as recommendation systems can have an effect on customer retention and sales. Customer profiling through basket analysis can allow for bundling of product promotions, better shelf spacing and positioning of product displays.
▪ Targeting the right customers	Bult and Wansbeek (1995); Elsner, Krafft, and Huchzermeier (2004); Gönül, Kim, and Shi (2000); Malthouse and Derenthal (2008)	Contact-strategy methods determine the optimal level of marketing contacts per customer. This strategy acknowledges the nonlinear relationship between marketing contacts and customer behavior. Scoring methods determine which customers will be selected for a campaign so as to maximize the return from the campaign.
▪ Offer timing and trigger events	Malthouse (2007)	Trigger events can be used to proactively initiate marketing contacts to retain customers who are likely to churn. They may also be applicable for customer expansion activities.
<i>Marketing actions</i>		
▪ Acquisition channel	Verhoef and Donkers (2005); Villanueva, Yoo, and Hanssens (2008)	Retained customer profitability is dependent on the customer's acquisition channel. For example, customers acquired through word-of-mouth are more profitable than customers acquired through firm initiated marketing. Customers acquired through a promotion or incentive are less profitable in the long run.
▪ Acquisition incentives	Lewis (2004)	Marketing contacts have a substantial impact on customer profitability. The influence of marketing is however nonlinear, i.e., too many contacts can be detrimental to customer-firm relationship. Optimizing marketing contacts based on customer responsiveness and targeting customers with a bundle of products has the potential to substantially increase firm profitability
▪ Marketing contacts	Rust and Verhoef (2005); Venkatesan and Kumar (2004); Kumar, Venkatesan, and Reinartz (2008); Kushwaha and Shankar (2007)	
<i>Marketing actions</i>		
▪ Cross-selling	Knott, Hayes, and Neslin (2002); Kumar, George, and Pancras (2007); Li, Sun, and Wilcox (2005)	Customers have a sequence of product acquisition with a firm. Models that can predict the customer's next product purchase can substantially improve the return on marketing efforts.
▪ Multichannel marketing	Ansari, Mela, and Neslin (2008); Neslin and Shankar (2009); Neslin et al. (2006b); Thomas and Sullivan (2005); Venkatesan, Kumar, and Ravishanker (2007); Kushwaha and Shankar (2007)	Customers who shop in multiple channels spend more and are more profitable than single channel customers. Marketing communications is a critical determinant of multichannel shopping. Customers use separate channels for browsing and shopping. Integration of product information and operations across channels is essential for customer retention.
▪ Loyalty programs	Leenheer et al. (2007); Liu (2008); Taylor and Neslin (2005)	Loyalty programs have a short and long-term influence on customer behavior. The short-term influence is however much larger than the long term influence. Customers are strategic and accelerate their purchases in anticipation of a reward.
<i>Customer outcomes</i>		
	Gupta and Zeithaml (2006); Reinartz and Kumar (2000); Petersen et al. (2009); Verhoef (2003)	Customer lifetime value is a more appropriate customer level outcome measure to measure the effectiveness of CRM activities because not all loyal customers are profitable. CRM actions can improve customer satisfaction, cross-buying and up-buying. Trust and commitment are key mediating factors between CRM actions and customer behavior.
<i>Firm value</i>		
	Gupta, Lehmann, and Stuart (2005)	Customer metrics are a good proxy for shareholder value. Firm value can be estimated as the sum of the value of all of the firm's existing and future customers.
<i>CRM implementation</i>		
▪ Performance	Reinartz, Krafft, and Hoyer (2004) Jayachandran et al. (2005) Ryals (2005)	A strategic framework is necessary for the success of CRM projects. An overall customer focus and the firm's acquisition and retention processes are related to customer satisfaction and firm performance. Buy-in from key stakeholders including employees is essential for the success of CRM activities.
▪ Implementation	Boulding et al. (2005) Bouma (2009)	

Sales force empowerment

In addition to getting customers to provide data, some retailers (e.g., furniture and automotive) need to also empower their sales representatives to gather and share customer data. Salespeople might be reluctant to do so because it is time consuming, it may decrease their autonomy and they may be unwilling to share information in fear of losing sales and commissions to others. Research in sales management, however, shows that the acceptance of CRM by sales representatives enhances targeting abilities, presentation skills and sales call productivity (Ahearne, Hughes, and Schillewaert 2007).

Data quality and reliability

There are many reasons for bad data quality such as the data being entered incorrectly, customers intentionally providing false data (i.e., wrong name, address), and customers not updating their information regularly. One bank discovered that over 5% of its customers for a certain product were born on November 11, 1911; the reason was that date of birth was a required field and the date “11/11/11” was easy for a banking representative to enter when the customer refused to provide the correct date.

Data quality and data integration are extremely difficult for multichannel retailers, which collect customer data across multiple channels. Ideally data should be integrated across channels to provide a complete view of customer activity and facilitate one-to-one marketing (Neslin et al. 2006b). Research has shown that data quality is positively related to performance (Zahay and Griffin 2002; Jayachandran et al. 2005), although Neslin et al. (2006b) argue that the marginal benefits of improved data quality will decrease while costs increase. This implies that the profit-maximizing level of data quality will be realized with not-perfect data. Despite their insights, there is limited empirical evidence on the optimal level of data quality and data integration. Moreover, cost of data quality and integration may not rise continuously, but may increase in a stepwise fashion. It is also important that different functions, such as marketing and service, have access to the same data.

Retailers with online channels have the opportunity to gather data that is potentially richer than traditional customer data, as customers' online browsing behavior can be followed extensively. These data are often referred to as click-stream data. More specifically, customers can be followed during their buying process from entering the website to finalizing the sale. Within marketing literature, multiple researchers have analyzed click-stream data with the objective of predicting when consumer website visits convert into purchase (Moe and Fader 2004), predict products that are viewed and purchased on a website (Moe 2006), and their browsing behavior within a website (Bucklin and Sismeiro 2003, 2009; Sismeiro and Bucklin 2004).

Future research

The rich data availability on websites and resulting behavioral targeting may create worries on privacy and poten-

tially may cause customer reactance (White et al. 2008). So far, research on consumer privacy has mainly been executed in the public policy domain. We believe that due to the noted developments in retail practice, privacy should gain more attention in the general marketing literature. Clearly, more research is also required on the optimal level of data quality and data integration across channels. So far, only conceptual insights are present, but can we infer an optimal level that may be contingent on customer strategies, customer behavior and competition? Yet another important research issue is how retailers can combine different data (e.g., POS, customer, and supplier data) to improve their marketing decision-making. Given that the amount of customer data is prodigious and that the data often is contradictory or at least inconsistent, it is difficult for store and company managers to uncover important relationships for improved decision-making. Though it is evident that sophisticated and intelligent technologies such as soft computing could help to leverage this potential of customer insights, more research is needed about the potential to apply intelligent technologies in retailing (Ravi, Raman, and Mantrala 2009). Finally, research on the topic of sales force empowerment in the retailing context is very limited. Given the importance of the sales force to ensure customer satisfaction as well as the cross-sell and up-sell of products, research on effectively using CRM technologies to improve sales force performance would be relevant and critical.

Data utilization — customer analytics

Utilizing the data to obtain customer insights is the next step in the CRM process (see Fig. 2). Analytical CRM systems promise to use data to send the *right offer* to the *right customers* at the *right time* (Shankar and Malthouse 2006, p. 3). This section outlines the different ways that retailers can use the data they are gathering in their CRM systems to accomplish these three goals.

Making the right offer

One approach to doing this is through customer (sub) segmentation (Malthouse and Calder 2006; Malthouse and Elsner 2006). Methodologically, the task of identifying sub-segments is similar to identifying market segments. There have been books written on such methodologies including cluster analysis, latent class analysis and finite mixture models (e.g., Bartholomew and Knott 1999; Wedel and Kamakura 2000; Everitt, Landau, and Leese 2001), but retailers often have additional types of data that are usually not used for doing traditional market segmentation. For example, many retailers have POS and loyalty club databases which create methodological challenges. Such data are collected over time and traditional market segmentation methods do not account for temporal aspects. Point-of-sale (POS) data with thousands or even tens of thousands of SKUs must be aggregated before clustering, but this is not an easy task. Consider, for example, the purchase of an 8 oz low-fat, vanilla, store-brand yogurt. This SKU indicates many different things about the customer. The

product category yogurt may indicate something about a person, the size is for individuals rather than bulk, it is low-fat rather than full-fat, it is a store rather than national brand, and the customer does not seem to like fruit. Automated procedures for grouping SKUs in meaningful ways are needed (Humby and Hunt 2003 hint at a process, but the details are not provided).

The right side of Fig. 1 shows that the process of segmenting customers so that a firm can create more relevant offers can be extended even further by creating offers for individual customers, or *segments of one*. Cost considerations imply that this will usually have to be done through a highly automated procedure such as those in recommendation systems. One stream of research analyzes the role of recommendation systems on consumer decision-making and has found that the quality of consumer decisions improves due to recommendation systems (Murray and Häubl 2009). Another stream is concerned with developing better recommendation systems by analyzing the best mapping of the ratings of a product from a population of consumers to develop and provide offers relevant to a single customer (Adomavicius and Tuzhilin 2005), and by incorporating consumer reactions to past recommendation offers (Bodapati 2008). Bucklin and Sismeiro (2009), and Iacobucci, Arabie, and Bodapati (2000) provide excellent reviews of research in recommendation systems and analytics related to click-stream data.

Beyond segmentation and personalization approaches, retailers also analyze POS data by profiling their customers and using market basket analysis (e.g., see DuMouchel and Pregibon 2001; Montgomery et al. 2004a,b; Reutterer et al. 2006). This helps the retailer understand which items are commonly bought together, as well as which items imply the purchase of other items (association rules). This information can help the retailer lay out the store and design promotional strategies.

Targeting the right customers

In CRM, retailers also have to decide on which customers to target with an offer. This is a common issue among retailers who use catalogs or other promotions that are targeted at individual customers such as email and direct mail. There is a very large and old literature devoted to this problem.

The targeting problem depends on whether the offer is to be used to acquire new customers or retain existing ones. We begin with acquisition. Many retailers rely heavily on mass advertising such as TV, print, and banner/display ads to acquire new customers. This is an unquestionably important approach for acquiring new customers, but does not lend itself so well to CRM and will therefore not be the focus of the discussion here.

In addition to mass advertising methods of acquisition, many retailers use direct marketing methods such as mail and email. Retailers “rent” mail or email addresses from list brokers (e.g., see www.nextmark.com). The main research questions are (1) which lists and (2) which names from a list, should a retailer rent (Courtheoux 2004)? In response to the first question, retailers do extensive testing of lists, but there is a need for theory to explain which external lists would be suitable for some

company to rent. To improve the selection of names within a list, some retailers use commercial segmentation systems such as Cohorts, Personix, or Prizm to identify names that are part of lifestage/style segments overrepresented in their own customer base. They also build “clone” models, which predict the likelihood of someone being a customer from variables that are available for the general public, such as demographic and lifestyle overlays. Clone models are a special type of scoring model, which will be discussed further below.

To decide which existing customers should receive an offer, retailers must choose between two general approaches: the contact-strategy and myopic “scoring-model” approaches. The contact-strategy approach, which was identified as an important research topic in the first issue of the *Journal of Interactive Marketing* (Kestnbaum, Kestnbaum, and Ames 1998), seeks to specify which combination of contacts each customer should receive so as to maximize the long-term profit from the customer. For example, suppose that a retailer will be mailing 6 catalogs over the next 6 months, and it wants to know which combination of the 6 it should send to each customer to maximize profit over this period. Sending multiple catalogs over a short period of time may cause them to cannibalize each other and may “wear out” the customer (Blattberg, Kim, and Neslin 2008, p. 744; Gönül, Kim, and Shi 2000). On the other hand, under-promoting a customer likely results in lost revenues and profits. Within this approach, numerous methods have been proposed (e.g., Bitran and Mondschein 1996; Gönül and Shi 1998; Gönül, Kim, and Shi 2000; Gönül and Ter Hofstede 2006; Campbell et al. 2001; Elsner, Krafft, and Huchzermeier 2004; Ching et al. 2004; Rust and Verhoef 2005; Simester, Sun, and Tsitsiklis 2006; Neslin et al. 2007). While some of these methods have been field tested (Kumar et al. 2008), more work is needed to compare different contact-strategy methods with each other as well as with myopic approaches.

Scoring models predict either the likelihood of response or the revenue generated from sending a customer some single contact. They are also used to predict other outcomes such as whether a customer will “churn” (e.g., see Neslin et al. 2006a; Risselada, Verhoef, and Bijmolt 2009; Xie et al. 2009) or the incremental value of a contact (Hansotia 2002). Sometimes they are included as a component within a contact-strategy model (e.g., Elsner, Krafft, and Huchzermeier 2004), but more often the predicted values – scores – are used to determine which customers should receive a contact in an attempt to maximize profit *from this contact*. Again, several variations of scoring models have been proposed (e.g., Bult 1993; Bult and Wansbeek 1995; Kumar, Rao, and Soni 1995; Haughton and Oulabi 1997; Colombo and Jiang 1999; Deichmann et al. 2002; Zahavi and Levin 1997a,b; Levin and Zahavi 1998, 2001; Suh, Noh, and Suh 1999; Malthouse 1999, 2001, 2002; Zadrozny and Elkan 2001; Bodapati and Gupta 2004; Ha, Cho, and MacLachlan 2005; Malthouse and Derenthal 2008).

Offer timing and trigger events

There are several ways that retailers can send offers at the right time. In some situations customers will develop in a

predictable way over time. For example, many of the needs of parents with young children change in a predictable way, starting with the needs of the expectant mother and progressing through infant, toddler, pre-schooler, etc. List brokers in the US rent “prenatal” database mailing lists. The Tesco supermarket chain in the UK has developed an extensive set of contacts including magazines with utilitarian advice designed to build their reputation as the store that meets all the needs of a family with young children, and promotions designed to close the sale.

Another way to approach the problem of offer timing is by detecting a *trigger event*, which is “something that happens during a customer’s lifecycle that a company can detect and portends the future behavior of the customer (Malthouse 2007).” Trigger events can portend good or bad futures. Suppose that a customer has been regularly shopping at a particular supermarket and suddenly stops shopping at the store (the trigger event). This trigger event could indicate that the relationship has ended and the supermarket should have reactive trigger contacts in place to resuscitate the relationship. An example of a trigger event that portends a positive future is when someone who had previously only flown occasionally with an airline starts flying more often. The airline should have trigger contacts in place towards whatever strategic goals it may have for the customer, perhaps locking in this “raising star’s” loyalty.

Future research

One important question concerns how many sub-segments should a retailer attempt to manage? The answer will depend on comparing the marginal cost of additional segments with the marginal revenue generated from being more relevant to customers, but it is not clear how to estimate such costs and revenues, in part because the incremental revenue due to having multiple versions rather than a single, one-size-fits-all offer depends on the quality of the versions that will be created. Another important research question is, which basis variables will produce sub-segmentations that will generate the largest incremental revenue? One group recommends using either historical or estimated future customer lifetime value (CLV) (e.g., Zeithaml, Rust, and Lemon 2001; Kumar, Ramani, and Bohling 2004; Kumar et al. 2009). Some suggest using estimates of share of wallet (e.g., Du, Kamakura, and Mela 2007). Other possible bases include the types of products purchased in the past, demographics and lifestyle variables, attitudes, or indicators of the type of shopping experience they seek. There are large literatures on many of these individual sets of basis variables. See Fader and Hardie (2009) and Blattberg, Malthouse, and Neslin (2009) for further discussion on estimating and using CLV. Hoffman and Novak (2009) and Calder, Malthouse, and Schaedel (2009) discuss the online experience and how to measure it. Future research on customer level metrics that are more appropriate for retailers and the different retailing business models would provide a useful contribution to the literature.

Many forms of advertising that have traditionally been considered mass are becoming more targeted. For example, in some markets different TV ads can be targeted at different

households (e.g., see Clifford 2009 and Marcus 2008), so that two neighbors could be watching the same TV program yet receive different ads. Also, the traditional advertising vehicles that many retailers rely on such as local newspapers are in steady decline and many are going out of business; local retailers will need to find new ways of reaching their customers and attracting prospects. The opportunities for targeting TV advertisement leads to interesting future research issues. One important question is, how does a retailer decide on the versions of ads to create? The answer to this question surely depends on segmentation and one-to-one personalization methods, as discussed above.

We also identify research opportunities concerning customer prediction. There are probabilistic theories and empirical studies for understanding which of the various statistical and machine learning models work best for certain situations (e.g., see Hastie, Tibshirani, and Friedman 2009). However, a better understanding is necessary for the issue of predicting customer behavior, which typically involves hundreds of thousands of observations, and a dependent variable with a very high percentage of zeros (for non-responses or purchased). Predictions from such models could also be improved with better data such as stronger predictive variables through better data sources and better “feature creation” from the transaction files that are used to form the predictor variables.

With regard to triggering customer events, there are research opportunities in developing automated ways of identifying and screening trigger events, operationalizing specific events (e.g., what constitutes a drop in the purchase rate?), understanding the root causes of the events, and developing effective trigger-response contacts.

Marketing actions

The next step in the CRM process is the application of marketing actions by a firm and its competition to develop profitable relationships with prospects and customers.

Prospects

Acquired prospects become part of the customer base and therefore affect the success of future retention campaigns and the value of the firm’s customer assets. Clarifying differences in the long-term consequences of acquisition campaigns thus offers guidance to managers about how they should acquire customers to maximize the long-term profitability of customers to the firm. The acquisition channel and the incentive provided to the prospects have been identified in the literature as major determinants of the long-term quality of the acquired customers. Recently retailers and manufacturers have started placing greater emphasis on acquiring customers through word of mouth. In fact, the popularity of WOM as an acquisition technique has led to development of intermediary firms such as buzzagent.com who recruit consumers that receive free product samples from manufacturers in return for talking about the products to other people in their social network.

Acquisition channel

Verhoef and Donkers (2005) found that for a Dutch financial services firm, retention and cross-buying vary significantly according to the type of acquisition channel that included mass media, direct marketing, Web site, and coinsurance. The effect was weaker on cross-buying than on retention, possibly because cross-buying requires a second step in the customer relationship, which is influenced by the firm's subsequent marketing interventions. In addition to a direct effect on customer behavior, acquisition channels also can have cross-effects on acquisition through other channels. For an online retailer, Villanueva, Yoo, and Hanssens (2008) find that customers acquired through marketing contribute more to the retailer's performance in the short term than do those acquired through word of mouth (WOM). The effect of marketing-induced acquisition settles down after only 3 weeks, whereas the WOM effect lasts for approximately 6 weeks.

Incentives

Several psychological theories about the negative consequences of promotional price discounts (e.g., coupons) are applicable for understanding the consequences of monetary incentives for customer acquisition on long-term profitability (e.g., Lewis 2006). For example, adaptation-level theory implies that a deeply discounted initial price leads to the formation of reference prices far below the regular price. Lewis (2006) analyzed the impact of price discounts used to acquire customers on the prices paid by those customers in future time periods in the context of newspaper subscribers and a cohort of customers acquired during the second quarter of an Internet retailer's operation. For both firms, acquisition discount depth negatively related to repeat buying rates and customer asset value.

Customers

Marketing contacts, loyalty programs, cross-selling and influences on multichannel shopping behavior represent some marketing actions that impact customer retention and growth.

Marketing contacts

Emerging empirical evidence indicates that marketing contacts through direct mail, telesales, and sales people are critical for influencing customer retention. In the business-to-business (B2B) context (Venkatesan and Kumar 2004; Reinartz, Thomas, and Kumar 2005; Venkatesan, Kumar, and Bohling 2007; Kumar et al. 2008), among financial services firms (Rust and Verhoef 2005) and in the pharmaceutical industry (Venkatesan, Reinartz, and Ravishanker 2009), marketing contacts through sales people, direct mail and telesales are found to influence customer retention, and profitability. However, the relative effectiveness of highly interpersonal salesperson contacts is greater than that of less interpersonal modes such as direct mail (Venkatesan and Kumar 2004; Reinartz, Thomas, and Kumar 2005). Recently, new interactive contact methods, such as marketing contacts through mobile phones and narrow casting, are getting attention in a

retailing. We refer to Shankar and Balasubramanian (2009) and Shankar et al. (2010) for an extensive discussion on mobile marketing opportunities.

However, many marketing contacts can be dysfunctional to a relationship (Fournier, Dobscha, and Mick 1998). In other words, too much contact can overload customers and lead to negative consequences, such as termination. This implies that the influence of marketing contacts is inverted U-shaped, which means an optimal level of marketing contacts exists and can ensure customer retention, but beyond that threshold, excessive marketing contacts can lead to customer inactivity (Venkatesan and Kumar 2004). Optimal investment levels that ensure customer retention therefore should match both a firm's objective to maximize profit and the threshold at which customers positively respond to marketing contacts.

Further, the influence and importance of marketing actions vary with the customer management objective. The level of investment that maximizes the acquisition rate for a firm differs from the investment levels required to maximize retention rates and customer profitability (Reinartz, Thomas, and Kumar 2005). Under spending is more detrimental and results in smaller returns on investment (ROI) than does overspending, and a suboptimal allocation of retention expenditures has a greater impact on long-term customer profitability than do suboptimal acquisition expenditures.

Cross-selling

Early cross-selling literature focused on aggregate outcomes of cross-selling activities, such as firm-level sales or store choice (Drèze and Hoch 1998; Chen et al. 1999). The importance of measuring individual customer outcomes in organizations, however, has shifted the focus to the effect of cross-selling on the individual level. Within this research realm, the order of product acquisition over time has been a key subject of inquiry. Two observations motivate researchers to predict product acquisition patterns. First, to implement a cross-selling strategy efficiently, managers need to know about the purchase patterns of each individual customer across various product categories. In other words, knowledge about cross-buying behavior should influence cross-selling strategies. Second, customers have predictable lifecycles and, as a result, purchase certain items before others. This predictable phenomenon provides the opportunity for firms to cross-sell additional products or services. Markets that are especially prone to this behavioral regularity include those in which consumers' wants or needs evolve after some preliminary consumption, consumers face some uncertainty about the quality of the product or service offering, or consumer learning is required to receive the full benefit of the product.

Li, Sun, and Wilcox (2005) find that bank customers usually invest more aggressively in financial instruments that promise stable returns (e.g., CDs, money market) after they obtain basic financial services (e.g., checking, savings, debit, credit, loan) and invest in high-risk, high-return brokerage accounts last. From the firm's perspective, it is natural to focus on determining the product or category with the highest purchase likelihood for each customer, and this element recently attracted attention in

the context of CRM strategies (Verhoef, Frances, and Hoekstra 2001; Knott, Hayes, and Neslin 2002; Kumar, Venkatesan, and Reinartz 2008). Both Knott, Hayes, and Neslin (2002) and Kumar, Venkatesan, and Reinartz (2008) show that tremendous upside potential for targeting customers with products they are ready to purchase in their next purchase cycle. Further, Knott, Hayes, and Neslin (2002) find that targeting retained customers is more profitable than targeting prospects.

Attempting to sell additional products or product lines can have detrimental impacts on a customer–firm relationship. First, frequent and wrongly targeted selling attempts are likely to increase customer resentment, which, in the worst case, results in the customer terminating the relationship. Second, unsuccessful attempts to increase the range of products with the customer are synonymous with resource misallocation. It is therefore critical to know not only what customers are most likely to buy next but also when they will buy the product of highest affinity. Further, targeting customers with the right product at the right time can lead to substantial improvements in the quality of the customer–firm relationship (Kumar, Venkatesan, and Reinartz 2008).

Loyalty programs

Loyalty programs, specifically points programs, seem to have a positive short-term impact on different aspects of customer behavior, including purchase frequency, basket size, lifetime duration and share of wallet (Liu 2008; Taylor and Neslin 2005). One major finding from multiple studies is that the impact of loyalty programs is more pronounced among light or moderate users rather than heavy users (Liu 2008; Lal and Bell 2003). The effect of loyalty programs on customer behavior might, however, be difficult to assess due to endogeneity issues (Leenheer et al. 2007). Few studies have also identified that loyalty programs have a long-term effect of increasing customer spending with a retailer, although the long-term effect is still smaller than the short-term effect (Liu 2008; Taylor and Neslin 2005).

Customized coupons differ from points programs in the sense that they are personalized for individual customers, and the retailers do not explicitly communicate to the customers the type of behaviors that are rewarded. Therefore, customized coupon campaigns have the ability to delight customers because of the unexpected nature of the rewards. In addition to rewarding customer behavior, customized coupon campaigns can also allow retailers to advertise their products, especially those in their assortment that are differentiated from competition. This advertising benefit of customized coupons can have a long-term positive impact on customer behavior (Van Heerde and Bijmolt 2005).

Recently, few studies have explored the profit implications of customizing coupons to individual customers. Through simulations, Rossi, McCulloch, and Allenby (1996) suggest that a customized coupon (where the face value of the coupon is customized to each individual) is more profitable than a blanket-mailed coupon. Extending this research, Pancras and Sudhir (2007) evaluate the optimal strategies for a customer data intermediary who facilitates the targeting and distribution of customized coupons that are funded by either a manufacturer or

a retailer, through the retail stores. They conclude that utilizing as much customer purchase history information as possible to select customers that receive a coupon, and allowing competing manufacturers to issue customized coupons simultaneously maximizes the profits for a customer data intermediary. Zhang and Wedel (2009) find that offline grocery stores have the potential to improve profits by customizing the face value of coupons to customer preferences at the mass-market level rather than customizing for individual customers.

Using a quasi field experiment conducted by a national grocery retailer, Venkatesan and Farris (2009) find that customized coupons are effective in increasing the gross profits per trip as well as the customer's trip frequency. They classify customized coupons into rewards focused, i.e., customized coupons that provide discounts on products purchased by the customer in the past, and cross-sell focused, i.e., customized coupons that provide discounts on products that the customer did not purchase in the past. The exposure effect, i.e., the brand information available in the customized coupon campaign, provided by both the reward and cross-sell focused customized coupon campaigns increase customer profitability. On the other hand, the redemption effect, i.e., the redemption of customized coupons, provided by the reward focused customized coupon campaigns decreases the future profitability of the customers. These results imply that retailers need to balance the positive exposure effect and the negative saving effect provided by the reward focused customized coupon campaigns.

Multichannel marketing

As mentioned earlier, a dramatic trend in the shopping environment in the past decade has been the proliferation of channels through which customers can interact with firms (Neslin et al. 2006b; Neslin and Shankar 2009). Consequently, CRM activities have grown increasingly complex as firms maintain and expand their customer relationships across multiple channels (Thomas and Sullivan 2005). This trend also has created a challenge for firms that want to manage their environment effectively, as well as opportunities for academics who want to produce insights that can help address these challenges. Preliminary evidence suggests that multichannel shopping can lead to higher customer profitability (Kushwaha and Shankar 2007; Venkatesan, Kumar, and Ravishanker 2007) and that marketing activities are influential in migrating customers across channels (Ansari et al. 2008). We refer to Dholakia et al. (2010) for a detailed discussion of consumer behavior insights in a multichannel retailing environment.

From a CRM perspective Payne and Frow (2005) argue that multichannel management is a key-element of CRM (see also Verhoef, van Doorn, and Dorotic 2007). This especially holds in a retailing environment, where firms, such as Tesco and LL Bean, use multiple channels to serve customers. We already mentioned the important issue of data integration across these channels. Importantly, it also impacts how marketing instruments should be applied across channels. For example, should promotions and prices be different across different channels? See Grewal et al. (2010) for detailed discussion on this topic.

Firms may also aim to steer customers to specific channels. For example, retail banks have steered customers to the Internet channel to reduce service costs. Moreover, some firms are confronted with the question how to continue with “old” channels. Former Dutch catalog firm Wehkamp.NL has now moved the vast majority of their customers to the Internet, and they now struggle with the question of how they should continue with the “old-fashioned” catalog. In essence, the new interactive Internet technology is disruptive for the old technology catalog and accompanies phone ordering. Could they stop sending catalogs, or would that negatively affect sales since many customers still use this channel for inspiration and it thus may strengthen the customer experience? For a strategic discussion on the effects of new interactive technologies on retail strategies, we refer to Varadarajan et al. (2010). For an overview of innovations in delivery of interactive services in the retailing context, see Berry et al. (2010). Neslin et al. (2006b) and Neslin and Shankar (2009) provide a very good overview of research and future research issues on multichannel marketing so there is no need to discuss this issue in great depth in this paper. Furthermore, Zhang et al. (2010) discuss issues relating to creating successful multichannel strategies in the retailing environment.

Future research

Evaluating how the acquisition techniques affect the long-term profitability of a firm seems like a ripe area for further research. Investigating the interaction of the acquisition message and acquisition channel has the potential to contribute to the literature. The response rate and ratio of profitable to unprofitable customers provided by an acquisition channel can also determine the level of resources managers should invest in each acquisition channel. Therefore, another area for additional research is the optimal trade-off between the level of price discount messages and product attribute/brand-building messages that can maximize overall firm profits. Yet another issue for further research is the efficacy of customer acquisition in different channel contexts. The impact of a retailer’s CRM activities on customer attitudes and the consequent impact of customer attitudes on profitability is a good avenue for future research (Venkatesan, Reinartz, and Ravishanker 2009). This stream of research would also provide a basis for investigating the interactions between investments in building brand equity versus investments that build customer equity. While there is substantial research on the benefits and strategies for cross-selling, there is very little research on the strategies for up-selling to customers.

Investigating the interaction of loyalty programs with other retail initiatives such as product assortment, and customer service would be a fruitful venue for future research. While analytical models predict that under competitive scenarios, retailers should not aim for perfect predictive capability of customer behavior (Chen, Narsimhan, and Zhang 2001), there is no empirical evidence regarding the impact of completion on the effectiveness of loyalty programs. Investigating the reasons multichannel customers provide higher profits also is necessary

to design effective multichannel marketing strategies. Several propositions, including increased loyalty, expansion of customer category requirements, self-selection, and pure marketing effect, have been advanced. These propositions require empirical verification (Neslin et al. 2006b; Neslin and Shankar 2009). Future research can investigate whether the adaptation-level theory tested in Lewis (2006) is applicable in other retailing settings beyond newspapers and online retailing.

Outcomes

The outcomes of marketing actions in data-rich retail environments are measured in many ways. Perhaps the most fundamental distinction among the many measured outcomes is whether the marketing action whose impact was being measured is tactical or strategic. Payne and Frow (2005) distinguish between CRM defined narrowly and tactically (implementation of a specific technology solution project) vs. CRM defined broadly and strategically (holistic approach to managing customer relationships to create shareholder value). At a strategic level, outcomes include *sustainable competitive advantage* (Rigby and Ledingham 2004), *a rallying point for the organization* (Rigby and Ledingham 2004; Berry 1995), *cannibalization*, *economies of scale*, *economies of scope*, *channel efficiency* (Neslin and Shankar 2009), and *financial returns* for the firm (Rigby and Ledingham 2004; Reinartz, Krafft, and Hoyer 2004).

Moving from comprehensive strategic outcome measures, the CRM literature provides us with a number of narrower, more tactical outcome measures. The most basic of these measures is *customer satisfaction* (B-to-C: Symanski and Hise 2000; Bolton, Kannan, and Bramlett 2000; B-to-B: Srinivasan and Moorman 2005; and Mithas, Krishnan, and Fornell 2005). The next most prevalent measures deal with customer *acquisition* and *retention*. Sirohi, McLaughlin, and Wittink (1998) and Reibstein (2002) show that one set of forces drive acquisition while a different set of forces drive retention.

Though Reichheld and Scheffer (2000) suggest that loyalty alone might be a sufficient goal for a firm, Reinartz and Kumar (2000) showed that long-life customers are not necessarily the most profitable customers. Consequently, focus has shifted to *profitable* customers, to maximizing *customer lifetime value*, *CLV* (Berry 1995; Berger and Nasr 1998; Reinartz and Kumar 2003; Venkatesan and Kumar 2004; Kumar and Shah 2004; Ryals 2005; and Kumar, Shah, and Venkatesan 2006) and to the link between CLV and traditional measures of *recency*, *frequency* and *monetary value* (Fader, Hardie, and Lee 2005). To build in consideration of the extent to which CLV can be expanded by the firm, Magi (2003) and Meyer-Waarden (2007) examine the pattern of consumer expenditure across competing outlets and how a retailer can expand the *share of wallet* it attracts. Also focused on expanding CLV, a number of studies examine *cross-buying* and *up-buying* (Verhoef, Frances, and Hoekstra 2001, 2002; Knott, Hayes, and Neslin 2002; Kumar, Venkatesan, and Reinartz 2006; Kumar, George, and Pancras 2007). Finally, from industry, we have the suggestion that CRM systems focus on the *rate of increase of customer equity*

(Rogers 2005). Petersen et al. (2009) provide a review of the metrics designed to manage loyalty and profitability.

Moving away from direct measures of customer profitability, a number of studies focus on *trust* as a key mediating variable (B2B: Morgan and Hunt 1994 and Doney and Cannon 1997; B2C: Berry 1995 and Sirdeshmukh, Singh, and Sabol 2002). In addition, we have studies that assume a lack of trust, examining customers' *free-riding* behavior (van Baal and Dach 2005) and *product return* behavior (Petersen and Kumar 2008; Anderson, Hansen, and Simester 2009).

All of the outcome measures presented up to this point are from the perspective of the retailer. A final body of relevant literature considers outcomes from the perspective of the customer. De Wulf, Odekerken-Schroder, and Iacobucci (2001) consider *consumers' perceptions of the retailer's investment in the relationship*. Sheth and Parvatiyar (1995) point out that consumers want *simplification of buying and information processing, reduced risk and cognitive consistency*. Gwinner, Gremler, and Bitner (1998) summarize by saying that consumers want *freedom from having to make decisions*. Noble and Phillips (2004) point out the mismatch between what retailers want from a "relationship" and what customers want from that "relationship." Fournier, Dobscha, and Mick (1998, p. 43) warn us that: "...[The] relationship between companies and consumers is troubled at best. When we talk to people about their lives as consumers, we do not hear praise for their so-called corporate partners. Instead, we hear about the confusing, stressful, insensitive, and manipulative marketplace in which they feel trapped and victimized."

Future research

In terms of future research directions, it makes sense to follow up on Fournier, Dobscha, and Mick's (1998) insight. Some current research (Venkatesan and Kumar 2004, Venkatesan, Kumar, and Bohling 2007) accommodate for nonlinear effects of marketing on customer behavior as a way to accommodate for the oversaturation effect proposed by Fournier et al. (1998). Research on other ways to design more customer-friendly CRM programs would be useful. What measures should CRM programs track and respond to? What would be the economic impact of such customer-friendly adjustments to a CRM program? Focusing on the more traditional outcome measures reviewed in this section, we note that most look backward (because they are based on a retailer's rich historical purchase data) and most also look inward (again, because they are based on a retailer's own data). Broadening the data used and measures constructed to create forward- and outward-looking measures of CLV should prove useful. Finally, customer relationship management should consider the link between customer equity and brand equity. Leone et al. (2006) point out that the value of a brand to a retailer should be related to the value of the customers who buy that brand from that retailer.

Link with firm value

Driven by the ongoing discussion on the role and contribution of the marketing function to firm performance (Verhoef

and Leeflang 2009), there remains an ongoing interest on how marketing strategies and outcomes are related to firm value and more specifically shareholder value (Srinivasan and Hanssens 2009). Researchers have shown that customer satisfaction, which can result from effective CRM activities, is positively related to firm value (e.g., Anderson, Fornell, and Mazvancheryl 2004). Recently, intensive scientific debates have stirred up about the validity of these findings (e.g., Jacobson and Mizik forthcoming; Fornell, Mithas, and Morgeson 2009; O'Sullivan, Hutchinson, and O'Connell 2009).

Gupta (2009) points out the importance of establishing the link between customer value and firm value. First, if the marketing function hopes to take on a more central role in the firm, marketing actions need to be linked to higher level metrics like firm value. Second, an understanding of the link between customer value and firm value can be useful to investors and to the financial community. Finally, establishing this link will demonstrate the forces that drive firm value. Wiesel, Skiera, and Villanueva (2008) propose that customer equity should be an integral part of financial reporting.

Gupta, Lehmann, and Stuart (2005) point out that one can estimate "firm value" (as determined in financial markets) as the sum of the value of all of its existing and future customers. They simplify that estimation by assuming that all customers have the same retention probability and that each consumer contributes the same amount of profit to the firm. They also take into the addition of new customers. Given those assumptions, a customer's lifetime value is customer profit times a "margin multiple," and that margin multiple is a simple function of retention rate and the firm's discount rate. They use their formula with publicly reported financial data to create estimates of firm value for several firms and show that those estimates are reasonable for some of the firms. Skiera, Wiesel, and Schulze (2009) extend the model of Gupta, Lehmann, and Stuart (2005) by also considering the effect of debt. Based on these studies Srinivasan and Hanssens (2009) propose that improvements in CLV (or customer equity) are significantly related to firm value.

Future research

Although the link between CLV and firm value has gained substantive attention in the marketing literature, there is a desperate need for more research on this issue. Especially, as the mentioned studies only consider a few cases and the results of these cases are not convincing. Gupta, Lehmann, and Stuart (2005) only find for three out of the five studied firms evidence for a link between CLV and shareholder value. Following Srinivasan and Hanssens (2009) we also assume that changes in customer equity are positively linked to firm value. Empirical evidence on this assumed relationship is, however, lacking. Only recently, Kumar and Shah (2009) show some initial evidence on how increases in CLV are positively related to changes in shareholder value for two firms. Future research should study this in much more depth and also aim to provide more empirical generalizations by studying a large number of firms. Another research issue in this important area concerns how economic recessions and expansions affect customer value

and how these changes relate to firm value (Deleersnyder et al. 2004). We propose that customer equity is negatively affected by economic recessions, but that this may depend on the value of current customer metrics. Firms with satisfied and loyal customers might be less affected.

CRM implementation and effectiveness in retailing

The discussed process so far shows how firms can use customer data to finally improve customer outcomes and firm value. Hereby we assume that firms will be able to implement such CRM. Experiences in practice have, however, shown that this is far from simple. Especially in the beginning of CRM, many projects failed (e.g., Rigby, Reichheld, and Scheffer 2002). Moreover, initially there was substantial discussion on whether a firms' CRM implementation would increase firm performance. Anecdotal evidence of firms as Tesco and Capital One indeed suggest that should be possible. Conceptually, Kim, Suh, and Hwang (2003) discuss how CRM should improve performance through increased loyalty, improved customer acquisition and decreasing customer costs. Verhoef and Lemon (forthcoming) discuss how CRM improves firm performance through improved customer-centricity, improving customer relationships, improved accountability and improved allocation of resources among customers. Reinartz, Krafft, and Hoyer

(2004) show that CRM acquisition and retention processes are related to firm performance. This relationship is, however, less strong when there is too much emphasis on CRM technology and software. Jayachandran et al. (2005) show how especially CRM information processes are positively related to customer outcomes, such as customer satisfaction and retention. Finally, findings of Ramani and Kumar (2008) reveal how a customer interaction focus, in which customer value management is an integral part, is also positively related to customer outcomes. Thus, there seems substantial conceptual and empirical evidence that CRM is positively related to firm performance either directly or through improved customer outcomes. However, the majority of studies are cross-sectional, and hence no causal relationships between CRM implementation and firm performance can be established. Only Ryals (2005) describe one case-study in which CLV before and after implementation is measured, showing an increase in CLV.

Literature on CRM implementations is rather scarce. Shah et al. (2006) have provided a conceptual discussion on the hurdles for firms to become customer centric. Choosing the right metrics is an important issue. Payne and Frow (2005) argue that CRM should be cross-functional and process-oriented in order to position CRM at strategic firm-level. Rigby, Reichheld, and Scheffer (2002) identified some perils in the implementation process. An important issue is that

Table 2
Future research topics and questions on CRM in retailing.

Topic	Substantive research questions	Analytic research questions
Data	<ul style="list-style-type: none"> ▪ How do customers react to the increasing availability and use of customer data in retailing? ▪ How do privacy concerns impact customer relationships with firms? ▪ How can POS data, customer data and supply chain be used to optimize retailing and marketing decisions? 	<ul style="list-style-type: none"> ▪ What is the optimal level of data quality and data integration across channel contingent on customer strategies, customer behavior and competition?
Data Utilization	<ul style="list-style-type: none"> ▪ Which factors drives customer triggers? 	<ul style="list-style-type: none"> ▪ What is the optimal number of sub segment a retailer should manage? ▪ Which variables are most useful for creating valuable sub-segments? ▪ Which data and methods can be used to target TV ads? ▪ Which of the various prediction methods for response, churn etc. performs best under which circumstances?
Marketing Actions	<ul style="list-style-type: none"> ▪ How do customers perceive CRM actions from a retailer firm and what are the resultant implications for retail strategy? ▪ What is the role of competition in retail CRM? 	<ul style="list-style-type: none"> ▪ What is the impact of the interactions among various CRM actions and the consequences of these interactions for optimal customer level resource allocation?
Customer Outcomes	<ul style="list-style-type: none"> ▪ Can a customer-friendly CRM system (i.e., a system that simplifies buying and information processing, reduces risk and provides psychological comfort) also be economically viable? Under what conditions? 	<ul style="list-style-type: none"> ▪ How can more forward- and outward-looking measures of customer value be constructed? ▪ How could you use measures of customer equity to create a measure of brand equity that is based on the value, to the retailer, of the customers who buy the brand?
Firm Value	<ul style="list-style-type: none"> ▪ What is the contribution of customer metrics in the valuation of a growing versus a mature firm? ▪ How are changes in customer value related to firm value? Why is this relationship absent in some cases, why is present in other cases? ▪ What is the impact of economic climate (i.e. recessions) on customer value? Do customer metrics (i.e. retention) reduce the presumed negative impact of recessions? 	<ul style="list-style-type: none"> ▪ What customer metrics should firms report for investors to better assess their value? ▪ How to allocate marketing costs in various channels including advertising and direct mail when computing customer lifetime value?
Implementation	<ul style="list-style-type: none"> ▪ Which factors determine the successful application of CRM within firms? 	<ul style="list-style-type: none"> ▪ What is the impact of CRM implementations on firm performance over time?

no customer strategy is created before the implementation. Rigby and Ledingham (2004) distinguish some characteristics of successful CRM implementations and argue that successful users have exhibited a healthy skepticism towards the promises of CRM. They also discuss that firms started with small CRM projects, and used that to continue with additional CRM projects. Empirically, top management attitude towards CRM, CRM ownership and alignment with key stakeholders is shown to correlate with CRM success (Bohling et al. 2006). Bouma (2009) empirically shows the importance of employee participation in creating successful CRM implementations. In sum, the discussed research is mainly conceptual and there is a lack of sound empirical studies showing the determinants of successful CRM implementations, while there is also a lack of research studying CRM implementations in a retailing context.

Future research

There is an urgent need for studies investigating the performance consequences of CRM on firm performance over time. We propose that CRM should have long-term consequences on firm performance, as it builds strategic assets that can create a long-term sustainable competitive advantage. However, the short-term consequences might be negative, given large investments, adaptations to new strategies and a strong focus on the technology. Event studies might be a possible way of investigating this issue. We also urge researchers to study the CRM implementation process and its' determinants of success in more depth. Insights from other disciplines, such as organizational behavior and change management, might be valuable in this respect. One proposition, based on our own experiences with firms and extant literature, is that CRM implementations that adopted strong customer-centric metrics as key-outcomes in the firm should be more successful.

Conclusion

In this paper, we discussed the role of CRM in retailing. Executing CRM in retailing is a challenging exercise. However, extant literature on CRM shows that performance gains can be enormous. We provided an overview of the literature that reflects the extensive knowledge base on CRM. Researchers have developed new models that offer deep insights on how marketing actions affect individual customer behavior. Based on this overview of the literature and our knowledge of CRM practice, we have outlined several opportunities for further research as summarized in Table 2. The enormous amount of customer data in retailing environments and the integration of channels, which now allow observation of online search behavior, will create new research challenges.

For retail managers, our overview of the literature provides useful insights on how to execute CRM in their daily practice. The availability of a vast amount of data, however, creates challenges. The academic literature has developed useful methods for targeting the right customers with the right offer

at the right time and for predicting future behavior and customer value. Furthermore, research has produced findings on how specific marketing actions affect customer performance. This knowledge can be used to improve marketing decision-making in the increasingly multichannel retail environment.

References

- Ackerman, Mark S., Lorrie F. Cranor, and Joseph Reagle (1999), "Privacy in E-commerce: Examining User Scenarios and Privacy Preferences," *Proceedings of the 1st ACM Conference on Electronic Commerce*, p. 1–8.
- Adomavicius, Gediminas and Alexander Tuzhilin (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, 734–49.
- Ahearne, Michael, Douglas E. Hughes, and Niels Schillewaert (2007), "Why Sales Reps Should Welcome Information Technology: Measuring the Impact of CRM-based IT on Sales Effectiveness," *International Journal of Research in Marketing*, 24, 336–49.
- Anderson, Eugene W., Claes Fornell, and Sanal K. Mazvancheryl (2004), "Customer Satisfaction and Shareholder Value," *Journal of Marketing*, 68, 126–41.
- Anderson, Eric T., Karsten Hansen, and Duncan Simester (2009), "The Option Value of Returns: Theory and Empirical Evidence," *Marketing Science*, 28, 405–23.
- Ansari, Asim and Carl F. Mela (2003), "E-Customization," *Journal of Marketing Research*, 40, 131–45.
- , ———, and Scott Neslin (2008), "Customer Channel Migration," *Journal of Marketing Research*, 45, 60–76.
- Arikan, Akin (2008), *Multichannel Marketing, Metrics and Methods for On and Offline Success*. Indianapolis, Indiana: John Wiley and Sons.
- Bartholomew, David and Martin Knott (1999), *Latent Variable Models and Factor Analysis*. 2nd ed. London: Arnold.
- Batra, Rajeev (1999), "Segmentation Analysis," In: Shepard D., editor. *The New Direct Marketing*. New York: McGraw-Hill. 288–301.
- Berger, Paul D. and Nada I. Nasr (1998), "Customer Lifetime Value: Marketing Models and Applications," *Journal of Interactive Marketing*, 12, 17–30.
- Berry, Leonard (1995), "Relationship Marketing of Services—Growing Interest, Emerging Perspectives," *Journal of the Academy of Marketing Science*, 23, 236–45.
- , Ruth N. Bolton, Cheryl H. Bridges, Jeffrey Meyer, A. Parasuraman, and Kathleen Seiders (2010), "Opportunities for Innovation in the Delivery of Interactive Retail Services," *Journal of Interactive Marketing*, 24, 2, 155–67.
- Bitran, Gabriel R. and Susana V. Mondschein (1996), "Mailing Decisions in the Catalog Industry," *Management Science*, 42, 1364–81.
- Blattberg, Robert C., Byung-Do Kim, and Scott A. Neslin (2008), *Database Marketing: Analyzing and Managing Customers*. New York: Springer.
- , Edward Malthouse, and Scott A. Neslin (2009), "Lifetime Value: Empirical Generalizations and Some Conceptual Questions," *Journal of Interactive Marketing*, 23, 2, 157–68.
- , Rashi Glazer, and John D.C. Little (1994), *Marketing Information Revolution*. Boston: Harvard Business School Press.
- Bodapati, Anand (2008), "Recommendation Systems with Purchase Data," *Journal of Marketing Research*, XLV, 77–93.
- and Sachin Gupta (2004), "A Direct Approach to Predicting Discretized Response in Target Marketing," *Journal of Marketing Research*, 41, 73–85.
- Bohling, Timothy, Douglas Bowman, Steve LaValle, Vikas Mittal, Das Narayandas, Girish Ramani, and Rajan Varadarajan (2006), "CRM Implementation: Effectiveness Issues and Insights," *Journal of Service Research*, 9, 184–94.
- Bolton, Ruth N., P.K. Kannan, and Matthew D. Bramlett (2000), "Implications of Loyalty Program Membership and Service Experiences for Customer Retention and Value," *Journal of the Academy of Marketing Science*, 28, 95–108.

- Boulding, William, Richard Staelin, Michael Ehret, and Wesley J. Johnston (2005), "A Customer Relationship Management Roadmap: What Is Known, Potential Pitfalls, and Where to Go," *Journal of Marketing*, 69, 155–66.
- Bouma, Jelle T. (2009), *Why Participation Works: The Role of Employee Participation in the Customer Relationship Management Type of Organizational Change*. SOM Research School: University of Groningen.
- Bucklin, Randolph E. and Sunil Gupta (2002), "Commercial Use of UPC Scanner Data: Industry and Academic Perspectives," *Marketing Science*, 18, 247–73.
- and Catarina Sismeiro (2003), "A Model of Web Site Browsing Behavior Estimated on Clickstream Data," *Journal of Marketing Research*, 40, 249–67.
- and ——— (2009), "Click Here for Internet Insight: Advances in Clickstream Data Analysis in Marketing," *Journal of Interactive Marketing*, 23, 1, 35–48.
- Bult, Jan Roelf (1993), "Semiparametric versus Parametric Classification Models: An Application to Direct Marketing," *Marketing Science*, 30, 380–90.
- and Tom Wansbeek (1995), "Optimal Selection for Direct Mail," *Marketing Science*, 14, 378–94.
- Calder, Bobby J. and Edward Malthouse (2005), "Managing Media and Advertising Change with Interactive Marketing," *Journal of Advertising Research*, 43, 356–61.
- , ———, and Schaedel, Ute (2009), "Engagement with Online Media and Advertising Effectiveness," technical report.
- Campbell, Deb, Randy Erdahl, Doug Johnson, Eric Bibelnicks, Michael Haydock, Mark Bullock, and Harlan Crowder (2001), "Optimizing Customer Mail Streams at Fingerhut," *Interfaces*, 31, 77–90.
- Chen, Yuxin, James D. Hess, Ronald Wilcox, and Z. John Zhang (1999), "Accounting Profits Versus Marketing Profits: A Relevant Metric for Category Management," *Marketing Science*, 18, 208–29.
- , Chakravarthi Narasimhan, and Z. John Zhang (2001), "Individual Marketing with Imperfect Targetability," *Marketing Science*, 20, 23–41.
- Ching, W.-K., M.K. Ng, K.K. Wong, and E. Altman (2004), "Customer Lifetime Value: Stochastic Optimization Approach," *Journal of the Operational Research Society*, 55, 860–8.
- Cigliano, James, Margaret Georgiadis, Darren Pleasance, and Susan Whalley (2000), "The Price of Loyalty," *McKinsey Quarterly*, 4, 68–77.
- Clifford, S. (2009), *Cable Companies Target Commercial to Audience*. Business section, March: The New York Times. 3).
- Colombo, Richard and Weina Jiang (1999), "A Stochastic RFM Model," *Journal of Interactive Marketing*, 13, 2–12.
- Courtheoux, Richard J. (2004), "Analysis of List Segmentation Efficacy and Campaign Optimization," *Journal of Interactive Marketing*, 18, 70–9.
- Davenport, Thomas H. and Jeanne G. Harris (2007), *Competing on Analytics: The New Science of Winning*. Boston: Harvard Business School Press.
- Deichmann, Joel, Abdolreza Eshghi, Dominique Haughton, Selin Sayek, and Nicholas Teebagy (2002), "Application of Multiple Adaptive Regression Splines (mars) in Direct Response Modeling," *Journal of Interactive Marketing*, 16, 15–27.
- Deleersnyder, Barbara, Marnik G. Dekimpe, Miklos Sarvary, and Philip M. Parker (2004), "Weathering Tight Economic Times: The Sales Evolution of Consumer Durables over the Business Cycle," *Quantitative Marketing and Economics*, 2, 347–83.
- De Wulf, Kristof, Gaby Odekerken-Schroder, and Dawn Iacobucci (2001), "Investments in Consumer Relationships: A Cross-Country and Cross-Industry Exploration," *Journal of Marketing*, 65, 33–50.
- Dholakia, Utpal M., Barbara E. Kahn, Randy Reeves, Aric Rindfleisch, David Stewart, and Earl Taylor (2010), "Consumer Behavior in a Multichannel, Multimedia Retailing Environment," *Journal of Interactive Marketing*, 24, 2, 86–95.
- Doney, Patricia M. and Joseph P. Cannon (1997), "An Examination of the Nature of Trust in Buyer–Seller Relationships," *Journal of Marketing*, 61, 35–51.
- Drèze, Xavier and Stephen Hoch (1998), "Exploiting the Installed Base Using Cross-merchandising and Category Destination Programs," *International Journal of Research in Marketing*, 15, 459–71.
- Dowling, Grahame R. and Mark Uncles (1997), "Do Customer Loyalty Programs Really Work?," *Sloan Management Review*, 38, 71–82.
- Du, Rex, Wagner Kamakura, and Carl Mela (2007), "Size and Share of Customer Wallet," *Journal of Marketing*, 71, 94–113.
- DuMouchel, William and Daryl Pregibon (2001), "Empirical Bayes Screening for Multi-Item Associations," In: Provost F., Srikant R., editors. Proceedings of KDD-2001. ACM. p. 67–76.
- Elsner, Ralf, Manfred Krafft, and Arnd Huchzermeier (2004), "Optimizing Rhenania's Direct Marketing Business through Dynamic Multilevel Modeling (DMLM) in a Multicatalog-brand Environment," *Marketing Science*, 23, 192–206.
- Everitt, Brian S., Sabine Landau, and Morven Leese (2001), *Cluster Analysis*. 4th ed. Arnold.
- Fader, Peter S., Bruce G.S. Hardie, and Ka. Lok Lee (2005), "RFM and CLV: Using Iso-Value Curves for Customer Base Analysis," *Journal of Marketing Research*, 42, 415–30.
- and ——— (2009), "Probability Models for Customer-base Analysis," *Journal of Interactive Marketing*, 23, 61–9.
- Fletcher, Keith (2003), "Consumer Power and Privacy: The Changing Nature of CRM," *International Journal of Advertising*, 22, 249–72.
- Fornell, Claes, Sunil Mithas, and Sunil Morgeson (2009), "The Statistical Significance of Portfolio Returns," *International Journal of Research in Marketing*, 26, 162–3.
- Fournier, Susan, Susan Dobscha, and David G. Mick (1998), "Preventing the Premature Death of Relationship Marketing," *Harvard Business Review*, 76, 42–51.
- Ganesan, Shankar, Morris George, Sandy Jap, Robert W. Palmatier, and Barton Weitz (2009), "Supply Chain Management and Retailer Performance: Emerging Trends, Issues and Implications for Research and Practice," *Journal of Retailing*, 85, 84–94.
- Gönül, Füsün and Meng Ze. Shi (1998), "Optimal Mailing of Catalogs: A New Methodology Using Estimable Structural Dynamic Programming Models," *Management Science*, 44, 1249–62.
- , Byung-Do Kim, and Meng Ze. Shi (2000), "Mailing Smarter to Catalog Customers," *Journal of Interactive Marketing*, 14, 2–16.
- and Frenkel Ter Hofstede (2006), "How to Compute Optimal Catalog Mailing Decisions," *Marketing Science*, 25, 65–74.
- Grewal, Dhruv, Michael Levy, and V. Kumar (2009), "Customer Experience Management in Retailing: An Organizing Framework," *Journal of Retailing*, 85, 1–14.
- , Ramkumar Janakiraman, Kirithi Kalyanam, P.K. Kannan, Brian Ratchford, Reo Song, and Stephen Tolerico (2010), "Strategic Online and Offline Retail Pricing: A Review and Research Agenda," *Journal of Interactive Marketing*, 24, 2, 138–54.
- Gupta, Sunil and Valerie Zeithaml (2006), "Customer Metrics and their Impact on Financial Performance," *Marketing Science*, 25, 718–39.
- , Donald R. Lehmann, and Jennifer A. Stuart (2005), "Valuing Customers," *Journal of Marketing Research*, 41, 7–18.
- (2009), "Customer-Based Valuation," *Journal of Interactive Marketing*, 23, 2, 169–78.
- Gwinner, Kevin P., Dwayne D. Gremler, and Mary Jo. Bitner (1998), "Relational Benefits in Service Industries: The Customer's Perspective," *Journal of the Academy of Marketing Science*, 26, 101–14.
- Ha, Kyoungnam, Sungzoon Cho, and Douglas MacLachlan (2005), "Response Models Based on Bagging Neural Networks," *Journal of Interactive Marketing*, 19, 17–30.
- Hansotia, Behram (2002), "Incremental Value Modeling," *Journal of Interactive Marketing*, 16, 35–46.
- Hastie, Trevor, Robert Tibshirani, and Jerome Friedman (2009), *The Elements of Statistical Learning*. 2nd ed. New York: Springer.
- Haughton, D. and S. Oulabi (1997), "Direct Marketing Modeling with Cart and CHAID," *Journal of Direct Marketing*, 11, 42–52.
- Hoffman, Donna L. and Thomas P. Novak (2009), "Flow Online: Lessons Learned and Future Prospects," *Journal of Interactive Marketing*, 23, 1, 23–34.
- Humbly, Clive and Terry Hunt (2003), *Scoring Points: How Tesco Is Winning Customer Loyalty*. London: Kogan Page.
- Iacobucci, Dawn, Phipps Arabia, and Anand Bodapati (2000), "Recommendation Agents on the Internet," *Journal of Interactive Marketing*, 14, 2–11.
- Jacobson, Robert and Natalie Mizik (forthcoming), "The Financial Markets and Customer Satisfaction: Reexamining the Value Implications of Customer

- Satisfaction from the Efficient Market Hypothesis”, *Marketing Science*, forthcoming.
- Jayachandran, Satish, Subhash Sharma, Peter Kaufman, and Pushkala Raman (2005), “The Role of Relational Information Processes and Technology Use in Customer Relationship Management,” *Journal of Marketing*, 69, 177–92.
- Kestnbaum, Robert D., Kate T. Kestnbaum, and Pamela W. Ames (1998), “Building a Longitudinal Contact Strategy,” *Journal of Interactive Marketing*, 12, 56–62.
- Kim, Jonghyeok, Euiho Suh, and Hyunseok Hwang (2003), “A Model for Evaluating the Effectiveness of CRM Using the Balanced Scorecard,” *Journal of Interactive Marketing*, 17, 5–19.
- Knott, Aaron I., Andrew Hayes, and Scott A. Neslin (2002), “Next-product-to-buy Models for Cross-Selling Applications,” *Journal of Interactive Marketing*, 16, 59–75.
- Kumar, Akhil, Vithala R. Rao, and Harsh Soni (1995), “An Empirical Comparison of Neural Network and Logistic Regression Models,” *Marketing Letters*, 6, 251–63.
- Kumar, V., Girish Ramani, and Timothy Bohling (2004), “Customer Lifetime Value Approaches and Best Practice Applications,” *Journal of Interactive Marketing*, 18, 60–72.
- and Denish Shah (2004), “Building and Sustaining Profitable Customer Loyalty for the 21st Century,” *Journal of Retailing*, 80, 317–30.
- and Werner Reinartz (2005), *Customer Relationship Management: A Databased Approach*. Chichester: John Wiley.
- , Rajkumar Venkatesan, and Werner Reinartz (2006a), “Knowing What to Sell, When, and to Whom,” *Harvard Business Review*, 84, 131–7.
- , Denish Shah, and Rajkumar Venkatesan (2006b), “Managing Retailer Profitability—One Customer at a Time!,” *Journal of Retailing*, 82, 277–94.
- , Morris George, and Joseph Pancras (2007), “Crossbuying in Retailing: Drivers and Consequences,” *Journal of Retailing*, 84, 15–27.
- , Rajkumar Venkatesan, Dennis Beckman, and Timothy Bohling (2008a), “The Power of CLV: Managing Customer Lifetime Value at IBM,” *Marketing Science*, 27, 585–99.
- , Rajkumar Venkatesan, and Werner Reinartz (2008b), “Performance Implications of Adopting a Customer Focused Sales Campaign,” *Journal of Marketing*, 72, 50–68.
- , Ilaria D. Pozza, J. Andrew Petersen, and Denish Shah (2009), “Reversing the Logic: The Path to Profitability through Relationship Marketing,” *Journal of Interactive Marketing*, 23, 2, 147–56.
- and Denish Shah (2009), “Expanding the Role of Marketing: From Customer Equity to Market Capitalization,” *Journal of Marketing*, 73, 119–36.
- Kushwaha, Tarun and Venkatesh Shankar (2007), “Optimal Multichannel Allocation of Marketing Efforts,” *MSI Report*, 07–207.
- Lal, Rajiv and David E. Bell (2003), “The Impact of Frequent Shopper Programs in Grocery Retailing,” *Quantitative Marketing and Economics*, 1, 179–202.
- Leenheer, Jorna, Harald J. van Heerde, Tammo H.A. Bijmolt, and Ale Smidts (2007), “Do Loyalty Programs Really Enhance Behavioral Loyalty? An Empirical Analysis Accounting for Self-selecting Members,” *International Journal of Research in Marketing*, 24, 31–47.
- Leone, Robert P., Vithala Rao, Kevin L. Keller, M. Anita, Leigh McAlister Luo, and Rajendra K. Srivastava (2006), “Linking Brand Equity to Customer Equity,” *Journal of Service Research*, 9, 125–38.
- Levin, Nissan and Jacob Zahavi (1998), “Continuous Predictive Modeling: A Comparative Analysis,” *Journal of Interactive Marketing*, 12, 5–22.
- and ——— (2001), “Predictive Modeling Using Segmentation,” *Journal of Interactive Marketing*, 15, 2–22.
- Lewis, Michael (2004), “The Influence of Loyalty Programs and Short Term Promotions on Customer Retention,” *Journal of Marketing Research*, 41, 281–92.
- (2006), “Customer Acquisition Programs and Customer Asset Value,” *Journal of Marketing Research*, 43, 195–204.
- Li, Shibo, Baohong Sun, and Ronald T. Wilcox (2005), “Cross-Selling Sequentially Ordered Products: An Application to Consumer Banking,” *Journal of Marketing Research*, 42, 233–9.
- Liu, Yuping (2008), “The Long Term Impact of Loyalty Programs on Consumer Purchase Behavior and Loyalty,” *Journal of Marketing*, 71, 19–35.
- Magi, Anne W. (2003), “Share of Wallet in Retailing: The Effects of Customer Satisfaction Loyalty Cards and Shopper Characteristics,” *Journal of Retailing*, 79, 97–106.
- Malthouse, Edward C. (1999), “Ridge Regression and Direct Marketing Scoring Models,” *Journal of Interactive Marketing*, 13, 10–23.
- (2001), “Assessing the Performance of Direct Marketing Scoring Models,” *Journal of Interactive Marketing*, 15, 49–62.
- (2002), “Performance-based Variable Selection for Scoring Models,” *Journal of Interactive Marketing*, 16, 37–50.
- (2003), “Database Sub-segmentation,” In: Iacobucci Dawn, Calder Bobby J., editors. *Kellogg on Integrated Marketing*. Wiley. p. 162–88.
- and Ralf Elsner (2006), “Customization with Cross-Basis Sub-segmentation,” *Journal of Database Marketing and Customer Strategy Management*, 14, 40–50.
- and Bobby J. Calder (2006), “CRM and Relationship Branding,” In: Tybout A., Calkins T., editors. *Kellogg on Branding*. Wiley. p. 150–68.
- (2007), “Mining for Trigger Events with Survival Analysis,” *Data Mining and Knowledge Discovery*, 15, 383–402.
- and Kirstin M. Derenthal (2008), “Improving Predictive Scoring Models through Model Aggregation,” *Journal of Interactive Marketing*, 22, 51–68.
- Marcus, C. (2008), “Reinvention of TV Advertising,” In: Calder Bobby J., editor. *Kellogg on Advertising and Media*. Wiley. p. 84–122.
- Meyer-Waarden, Lars (2007), “The Effects of Loyalty Programs on Customer Lifetime Duration and Share of Wallet,” *Journal of Retailing*, 83, 223–36.
- Milne, George R. and Maria-Eugenie Boza (2000), “Trust and Concern in Consumers’ Perceptions of Marketing Information Management Practices,” *Journal of Interactive Marketing*, 13, 5–24.
- Mithas, Sunil, M.S. Krishnan, and Claes Fornell (2005), “Why Do Customer Relationship Management Applications Affect Customer Satisfaction?,” *Journal of Marketing*, 69, 201–9.
- Moe, Wendy M. and Peter Fader (2004), “Capturing Evolving Visit Behavior in Clickstream Data,” *Journal of Interactive Marketing*, 18, 5–19.
- (2006), “Capturing Evolving Visit Behavior in Clickstream Data,” *Journal of Marketing Research*, 43, 680–92.
- Montgomery, Alan, Shibo Li, Kannan Srinivasan, and John Liechty (2004a), “Modeling Online Browsing and Path Analysis Using Clickstream Data,” *Marketing Science*, 23, 579–95.
- , Kartik Hosanagar, Ramayya Krishnan, and Karen Clay (2004b), “Designing a Better Shopbot,” *Management Science*, 50, 189–206.
- and Michael Smith (2009), “Prospects for Personalization on the Internet,” *Journal of Interactive Marketing*, 23, 2, 130–7.
- Morgan, Robert and Shelby D. Hunt (1994), “The Commitment–Trust Theory of Relationship Marketing,” *Journal of Marketing*, 58, 20–38.
- Murray, Kyle and Gerald Häubl (2009), “Personalization without Interrogation: Towards More Effective Interactions between Consumers and Feature-Based Recommendation Agents,” *Journal of Interactive Marketing*, 23, 2, 138–46.
- Neslin, Scott A., Sunil Gupta, Wagner Kamakura, Junxiang X. Lu, and Charlotte Mason (2006a), “Defection Detection: Measuring and Understanding the Predictive Accuracy of Customer Churn Models,” *Journal of Marketing Research*, 43, 204–11.
- , Dhruv Grewal, Robert Leghorn, Venkatesh Shankar, Marije L. Teerling, Jacquelyn S. Thomas, and Peter C. Verhoef (2006b), “Challenges and Opportunities in Multichannel Customer Management,” *Journal of Service Research*, 9, 95–112.
- , Thomas P. Novak, Kenneth R. Baker, and Donna L. Hoffman (2007), “An Optimal Contact Model for Maximizing Online Panel Response Rates,” working paper, Tuck School of Business, Dartmouth College, Hanover, NH.
- and Venkatesh Shankar (2009), “Key Issues in Multichannel Management: Current Knowledge and Future Directions,” *Journal of Interactive Marketing*, 23, 1, 70–81.
- Noble, Stephanie M. and Joanna Phillips (2004), “Relationship Hindrance: Why Would Consumers Not Want a Relationship with a Retailer?,” *Journal of Retailing*, 80 (289–30).
- O’Sullivan, Don, Mark C. Hutchinson, and Vincent O. O’Connell (2009), “Empirical Evidence of the Stock Market’s (Mis)pricing of Customer Satisfaction,” *International Journal of Research in Marketing*, 26, 154–61.

- Pancras, Joseph and K. Sudhir (2007), "Optimal Marketing Strategies for a Customer Data Intermediary," *Journal of Marketing Research*, 44, 560–78.
- Payne, Adrian and Pennie Frow (2005), "A Strategic Framework for Customer Relationship Management," *Journal of Marketing*, 69, 167–74.
- Peltier, James, George Milne, and Joseph Phelps (2009), "Information Privacy Research: Framework for Integrating Multiple Publics, Information Channels, and Responses," *Journal of Interactive Marketing*, 23, 2, 191–205.
- Peppers, Don and Martha Rogers (1997), *The One-to-One Future: Building Relationships One Customer at a Time*. New York: Doubleday.
- Petersen, J. Andrew and V. Kumar (2008), "Are Product Returns a Necessary Evil? The Antecedents and Consequences of Product Returns," working paper, University of North Carolina, Chapel Hill.
- , Leigh McAlister, David J. Reibstein, Russell S. Winer, V. Kumar, and Geoff Atkinson (2009), "Choosing the Right Metrics to Maximize Profitability and Shareholder Value," *Journal of Retailing*, 85, 84–94.
- Ramani, Girish and V. Kumar (2008), "Interaction Orientation and Firm Performance," *Journal of Marketing*, 72, 27–45.
- Ravi, Vadlamani, Kalyan Raman, and Murali K. Mantrala (2009), "Applications of Intelligent Technologies in Retail Marketing." In: Krafft Manfred, Mantrala M.K., editors. *Retailing in the 21st Century*. 2nd ed. Springer. p. 173–87.
- Reibstein, David J. (2002), "What Attracts Customers to Online Stores and What Keeps them Coming Back?," *Journal of the Academy of Marketing Science*, 30 (475–473).
- Reichheld, Frederick F. and Paul Scheffer (2000), "E-loyalty: Your Secret Weapon on the Web," *Harvard Business Review*, 78, 105–13.
- Reinartz, Werner J. and V. Kumar (2000), "On the Profitability of Long-life Customers in a Non-contractual Setting: An Empirical Investigation and Implications for Marketing," *Journal of Marketing Research*, 41, 17–35.
- and ——— (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration," *Journal of Marketing*, 67, 77–99.
- , Manfred Krafft, and Wayne D. Hoyer (2004), "The Customer Relationship Management Process: Its Measurement and Impact on Performance," *Journal of Marketing Research*, 41, 293–305.
- , Jacquelyn S. Thomas, and V. Kumar (2005), "Balancing Acquisition and Retention Resources to Maximize Customer Profitability," *Journal of Marketing*, 69, 63–79.
- Reutterer, Thomas, Andreas Mild, Martin Natter, and Alfred Taudes (2006), "A Dynamic Segmentation Approach for Targeting and Customizing Direct Marketing Campaigns," *Journal of Interactive Marketing*, 20, 43–57.
- Rigby, Darrell K., Frederick F. Reichheld, and Paul Scheffer (2002), "Avoid the Four Perils of CRM," *Harvard Business Review*, 80, 101–9.
- and Dianne Ledingham (2004), "CRM Done Right," *Harvard Business Review*, 82, 118–29.
- Risselada, Hans, Peter C. Verhoef, and Tammo H. A. Bijmolt (2009), "Parameter Stability and Staying Power of Churn Prediction Models," working paper, University of Groningen.
- Rust, Roland T. and Peter C. Verhoef (2005), "Optimizing the Marketing Interventions Mix in Intermediate-Term CRM," *Marketing Science*, 24, 477–89.
- Rogers, Martha (2005), "Customer Strategy: Observations from the Trenches," *Journal of Marketing*, 69, 262–3.
- Rossi, Peter E., Robert McCulloch, and Greg M. Allenby (1996), "The Value of Purchase History Data in Target Marketing," *Marketing Science*, 15, 321–40.
- Ryals, Lynette (2005), "Making Customer Relationship Management Work: The Measurement and Profitable Management of Customer Relationships," *Journal of Marketing*, 69, 252–61.
- Shah, Denish, Roland T. Rust, A. Parasuraman, Richard Staelin, and George S. Day (2006), "The Path to Customer Centricity," *Journal of Service Research*, 9, 113–24.
- Shankar, Venkatesh and Edward Malhouse (2006), "Moving Interactive Marketing Forward," *Journal of Interactive Marketing*, 20, 2–4.
- and Sridhar Balasubramanian (2009), "Mobile Marketing: A Synthesis and Prognosis," *Journal of Interactive Marketing*, 23, 2, 118–29.
- , Alladi Venkatesh, Charles Hofacker, and Prasad Naik (2010), "Mobile Marketing in the Retailing Environment: Current Insights and Future Research Avenues," *Journal of Interactive Marketing*, 24, 2, 111–20.
- Sheth, Jagdish N. and Atul Parvatiyar (1995), "Relationship Marketing in Consumer Markets: Antecedents and Consequences," *Journal of the Academy of Marketing Science*, 23, 255–71.
- Shugan, Steven M. (2005), "Brand Loyalty Programs: Are They Shams?," *Marketing Science*, 24, 185–93.
- Simester, Duncan I., Peng Sun, and John N. Tsitsiklis (2006), "Dynamic Catalog Mailing Policies," *Management Science*, 52, 683–96.
- Sirdeshmukh, Deepak, Jagdip Singh, and Barry Sabol (2002), "Consumer Trust, Value, and Loyalty in Relational Exchanges," *Journal of Marketing*, 6, 15–37.
- Sirohi, Niren, Edward W. McLaughlin, and Dick R. Wittink (1998), "A Model of Customer Perceptions and Store Loyalty Intentions for a Supermarket Retailer," *Journal of Retailing*, 74, 223–45.
- Sismeiro, Catarina and Randolph E. Bucklin (2004), "Modeling Purchase Behavior at an E-Commerce Web Site: A Task-Completion Approach," *Journal of Marketing Research*, 41, 306–23.
- Skiera, Bernd, Thorsten Wiesel, and Christian Schulze (2009), "Customer-Based Firm Valuation", working Paper, University of Groningen.
- Smit, Willem J. (2006), "Market Information Sharing in Channel Relationships: Its Nature, Antecedents, and Consequences," dissertation, Erasmus Research Institute in Management, Rotterdam.
- Srinivasan, Raji and Christine Moorman (2005), "Strategic Firm Commitments and Rewards for Customer Relationship Management in Online Retailing," *Journal of Marketing*, 69, 255–71.
- Srinivasan, Shuba and Dominique M. Hanssens (2009), "Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions," *Journal of Marketing Research*, 46, 293–313.
- Suh, E.H., K.C. Noh, and C.K. Suh (1999), "Customer List Segmentation Using the Combined Response Model," *Expert Systems with Applications*, 17, 89–97.
- Symanski, David M. and Richard T. Hise (2000), "E-Satisfaction: An Initial Examination," *Journal of Retailing*, 76, 309–22.
- Taylor, Gail A. and Scott Neslin (2005), "The Current and Future Sales Impact of a Retail Frequency Reward Program," *Journal of Retailing*, 81, 293–305.
- Thomas, Jacquelyn S. and Ursula Sullivan (2005), "Managing Marketing Communications with Multichannel Customers," *Journal of Marketing*, 69, 239–51.
- van Baal, Sebastian and Christian Dach (2005), "Free Riding and Customer Retention Across Retailers' Channels," *Journal of Interactive Marketing*, 19, 75–85.
- van Doorn, Jenny, Peter C. Verhoef, and Tammo H.A. Bijmolt (2007), "The Importance of Non-linear Relationships between Attitude and Behavior in Policy Research," *Journal of Consumer Policy*, 30, 75–90.
- van Heerde, Harald J. and Tammo H.J. Bijmolt (2005), "Decomposing the Promotion Revenue Bump Due for Loyalty Program Members versus Nonmembers," *Journal of Marketing Research*, 42, 443–57.
- Varadarajan, Rajan, Raji Srinivasan, Gautham Gopal Vadakkepatt, Manjit S. Yadav, Paul A. Pavlou, Sandeep Krishnamurthy, and Tom Krause (2010), "Interactive Technologies and Retailing Strategies: A Review, Conceptual Framework and Future Research Directions," *Journal of Interactive Marketing*, 24, 2, 96–110.
- Venkatesan, Rajkumar and V. Kumar (2004), "A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy," *Journal of Marketing*, 68, 106–25.
- , ———, and Timothy Bohling (2007a), "Optimal CRM Using Bayesian Decision Theory: An Application to Customer Selection," *Journal of Marketing Research*, 44, 579–94.
- , ———, and Nalini Ravishanker (2007b), "Multichannel Shopping: Causes and Consequences," *Journal of Marketing*, 71, 114–32.
- , Werner Reinartz, and Nalini Ravishanker (2009), "Attitudes Towards Firm and Competition: How Do They Matter for CRM Activities," working paper, Darden Graduate School of Business, University of Virginia.
- and Paul Farris (2009), "Do Retail Customers Reward Customized Coupon Programs," working paper, Darden Graduate School of Business, University of Virginia.
- Verhoef, Peter C., Philip Hans Frances, and Janny C. Hoekstra (2001), "The Impact of Satisfaction and Payment Equity on Cross-Buying: A Dynamic Model for a Multiservice Provider," *Journal of Retailing*, 77, 359–78.

- , Philip Hans Frances, and Janny C. Hoekstra (2002), “The Effect of Relational Constructs on Customer Referrals and Number of Services Purchased from a Multiservice Provider: Does Age of Relationship Matter,” *Journal of the Academy of Marketing Science*, 30, 202–16.
- (2003), “Understanding the Effect of Customer Relationship Management Efforts on Customer Retention and Customer Share Development,” *Journal of Marketing*, 67, 30–45.
- , Pennie N. Spring, Janny C. Hoekstra, and Peter S.H. Leeflang (2003), “The Commercial Use of Segmentation and Predictive Modeling Techniques for Database Marketing in The Netherlands,” *Decision Support Systems*, 34, 471–81.
- and Bas Donkers (2005), “The Effect of Acquisition Channels on Customer Loyalty and Cross-buying,” *Journal of Interactive Marketing*, 19, 31–43.
- , Scott A. Neslin, and Björn Vroomen (2007a), “Multichannel Customer Management: Understanding the Research Shopper Phenomenon,” *International Journal of Research in Marketing*, 24, 129–48.
- , Jenny van Doorn, and Matilda Dorotic (2007b), “Customer Value Management: An Overview and Research Agenda. Marketing,” *Journal of Research in Management*, 2, 51–69.
- , Katherine N. Lemon, A. Parasuraman, Anne Roggeveen, Michael Tsiros, and Leonard A. Schlessinger (2009), “Customer Experience Creation: Determinants, Dynamics and Management Strategies,” *Journal of Retailing*, 85, 31–41.
- and Peter S.H. Leeflang (2009), “Understanding the Marketing Departments’ Influence within the Firm,” *Journal of Marketing*, 72, 14–37.
- and Katherine N. Lemon (forthcoming), “Advances in Customer Value Management” in *Handbook of Relationship Marketing*, Janet Parish, Robert M. Morgan, and G. Deitz, eds.
- Villanueva, Julian, Shijin Yoo, and Dominique Hanssens (2008), “The Impact of Marketing-Induces vs. Word-of-Mouth Customer Acquisition on Customer Equity Growth,” *Journal of Marketing Research*, 45, 48–59.
- Wedel, Michel and Wagner Kamakura (2000), *Market Segmentation: Conceptual and Methodological Foundations*. Kluwer.
- White, Tiffany B., Debra L. Zahay, Helge Thorbjørnsen, and Sharon Shavitt (2008), “Getting Too Personal: Reactance to Highly Personalized Email Solicitations,” *Marketing Letters*, 19, 39–50.
- Wiesel, Torsten, Bernd Skiera, and Julian Villanueva (2008), “Customer Equity: An Integral Part of Financial Reporting,” *Journal of Marketing*, 72, 1–14.
- Xie, Yaya, Xiu Li, E.W.T. Ngai, and Weiyun Ying (2009), “Customer Churn Prediction Using Improved Balanced Random Forests,” *Expert Systems with Applications*, 36, 5445–9.
- Zadrozny, Bianca and Charles Elkan (2001), “Learning and Making Decisions when Costs and Probabilities Are Both Unknown,” In: Provost F., Srikant R., editors. Proceedings of KDD-2001. ACM. p. 204–13.
- Zahavi, Jacob and Nissan Levin (1997a), “Applying Neural Computing to Target Marketing,” *Journal of Direct Marketing*, 11, 5–22.
- and —— (1997b), “Issues and Problems in Applying Neural Computing to Target Marketing,” *Journal of Direct Marketing*, 11, 63–75.
- Zahay, Debra and Abbie Griffin (2002), “Are Customer Information Systems Worth It? Results from B2B Services,” Report No. 02-113. Marketing Science Institute.
- Zhang, Jie and Michel Wedel (2009), “The Effectiveness of Customized Promotions in Online and Offline Stores,” *Journal of Marketing Research*, 46, 190–206.
- Zhang, Jie, Paul W. Farris, John W. Irvin, Tarun Kushwaha, Thomas J. Steenburgh, and Barton A. Weitz (2010), “Crafting Integrated Multi-channel Retailing Strategies,” *Journal of Interactive Marketing*, 24, 2, 168–80.
- Zeithaml, Valerie A., Roland T. Rust, and Katherine N. Lemon (2001), “The Customer Pyramid: Creating and Serving Profitable Customers,” *California Management Review*, 43, 118–42.