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## Revisiting the Use of Customer Information for CRM

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# Revisiting the Use of Customer Information for CRM

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# Revisiting the Use of Customer Information for CRM

## **Abstract**

For the past decade, customer relationship management (CRM) has been one of the priorities in marketing research and practice. However, many of the CRM systems did not perform as the companies expected. As such shortcoming could be due to inappropriate data input, this study provides a comprehensive overview of the empirical CRM literature. Along the phases of the CRM process, the authors show which kind of data has successfully proven to achieve the CRM objectives. The study provides researchers with a review of the empirical research on CRM and allows practitioners insights on the usability of customer data for CRM.

## 1 Introduction

For the past decade, *customer relationship management* (CRM) has been one of the top priorities in both marketing research and practice. This term refers to a customer-oriented management approach that involves the integration, synchronization, and optimization of all processes relevant to customers, with the customer in the center of all activities (Ryals 2005). Thus, various studies have proven the positive impact of such CRM activities on business growth (Day and Van den Bulte 2002; Zahay and Griffin 2002), market share (Schoder and Madeja 2004; Jayachandran, Sharma, Kaufman, and Raman 2005), profitability (Cao and Gruca 2005; Kim, Suh, and Hwang 2003), customer satisfaction (Stefanou, Sarmaniotis, and Stafyla 2003; Croteau and Li 2003), and loyalty (Colgate and Danaher 2000; Gustafsson, Johnson, and Roos 2005). However, the practical impact of CRM on success has been challenged as the results obtained do not correspond with companies expectations (Rigby, Reichheld and Schefter 2002; Zablah, Bellenger, and Johnston 2004), there are reports of 70% of all CRM implementations being experienced as failures (Gartner Group 2003).

The success of CRM mainly depends on the information that enters the CRM system. Therefore, one reason for the discrepancy between expectations and reality could be due to the customer data that is used for the analyses - e.g., if the data companies utilize are only able to contribute minimally or not at all to their objectives or relevant data are simply not used. Fifteen interviews with customer managers from T-Online, Gruner+Jahr, Burda, Springer, Otto, b+m Informatik, and Manufaktum, revealed that a major issue for all managers appeared to be identifying the relevant customer data out of the massive amounts of existing and potential data. Therefore, the scope of this study is to give an overview of how customer information have empirically been found to contribute to the success of CRM based and what CRM objectives management may reasonably expect to be met from available customer information.

The objectives of CRM depend on the distinct phases of the customer life cycle (Becker, Greve, and Albers 2009). Dwyer et al. (1987) report that customer relationships evolve through different phases as companies interact with customers (Srivastava, Shervani, and Fahey 1998). Thus, Reinartz et al. (2004) differentiate between the initiation, expansion, and termination phase. Gaining new customers and winning back lost ones is the focus of the *initiation phase* (Thomas, Blattberg, and Fox 2004). As the relationship with successfully recaptured customers (re-)commences, activities to win back customers are equally considered to be an objective of the initiation phase.

A customer who makes frequent purchases, either by buying the same product repeatedly or by expanding his or her scope of utilization to other products, is in the *maintenance phase* of their customer relationship (Stauss 2004). The main emphasis of this phase is the development and stabilization of the customer relationship through targeted customer retention strategies (Diller 1998; Homburg and Schäfer 2002; Müller 2004).

In the *termination phase*, the turning point of a customer's sales curve is reached; in other words, customer sales will only rise with decreasing growth rates, or may even decline. The challenge lies in using the appropriate methods of analysis to identify inactive customers or customers with a high probability of defection (Reinartz and Kumar 2000) in order to decide whether an existing customer relationship should be maintained or terminated. Should the relationship be deemed unprofitable, companies will actively take steps to terminate it (*Demarketing*; see Kotler and Levy 1971; Blömeke and Clement 2009), thus ending the customer's life cycle (Dwyer, Schurr, and Oh 1987). If, on the other hand, customers are found to be profitable yet inactive, first-phase recapturing activities will be initiated.

According to Payne and Frow (2005, p. 168), CRM is only able to reach its phase-specific objectives if properly supported by technologies, applications, and adequate information. Since the technological component of CRM is widely available to companies as a default solution (Hitt and Brynjolfsson 1996; Kale 2004; Zahay and Griffin 2004), the results depend on the input quality (i.e., available customer information). Based on their origin, customer data are classified into basic data, purchase data, action data and reaction data (Link and Hildebrand 1993, p. 377 et seq.).

As summarized in Figure 1, *basic data* is comprised of customer contact data, as well as demographic, geographic, and psychographic background information which is often used by a company to segment customers (e.g., Kumar and Reinartz 2006; Payne 2006). *Purchase data* contains information about the customers' actual purchase behavior, including the duration of the customer relationship, the time, quantity, and value of previous purchases, as well as purchase frequency (Kumar and Reinartz 2006; Homburg and Sieben 2005). These data are collected regularly and used as the basis for targeted marketing strategies (Rossi, McCulloch, and Allenby 1996).

A companies' *marketing action data* (in the following: action data) is comprised of all individual customer communication activities including timing, nature, frequency, intensity, and costs (Homburg and Sieben 2005; Kumar and Venkatesan 2005). The extent to which these activities actually evoke a customer response is denoted in *reaction data*. Therefore, *reaction data* is related to action data and contains information about the reactions of potential or actual customers to the company's marketing strategies (Link and Hildebrand 1993, p. 37 et seq.). Participation in loyalty programs and usage of decision guidance, i.e., the

acceptance/use of a company's recommendations as well as reclamations and returns are also included in *reaction data*.

Figure 1: Illustration of customer data

Basic Data		
<i>Demographic Data</i>	<i>Geographic Data</i>	<i>Psychographic Data</i>
Age	Residence / Residence of company	<i>B2C</i>
Gender	Zip code	Interests
Nationality	Location	Recreational activities
Marital status	Population density	Opinions
Number of children	Climate	Attitude / Merits
Income		Usage habits (e.g., recreation and purchase behavior, internet usage)
Educational level		<i>B2B</i>
Profession		Branch membership
Size of household		Company size
(Social) Class		
Purchase Data	(Marketing) Action Data	Reaction Data
Frequency *	Direct mailings (catalogs, emails)	Usage of monetary advantages
Recency	Direct promotions (e.g., by email, SMS, mail)	Subscriptions to newsletters
Monetary value	Loyalty programs	Voucher/ Coupon usage
Return quotes	Recommendation programs	Lottery participation
Preferred distribution channels		Participation in loyalty programs
Cross-buying activities		Adoption of Recommendations
		Use of decision support
		Customer complaints / returns

\* Purchase or usage (service)

However, many companies still struggle to concretely identify the customer data which can be used as *control measures* in different phases of a customer relationship (e.g., by measuring the effectiveness for implementing actions and optimizing campaigns), or is relevant for the analysis of customer behavior (e.g., by means of determining customer profitability, Customer Lifetime Values (CLV) and Customer Equity).

To the best of our knowledge, no previous study has provided a systematic overview of the relevant variables identified in empirical marketing research thus far and summarized their success for different CRM goals. Therefore, this article focuses on two key problems. First, we investigate which customer data has been proven to be relevant for the individual phases of the CRM process and their respective aims. We especially look at which customer data, collected on new and existing customers, are relevant for the analysis and prediction of customer behavior, particularly focusing on E-CRM. Second, we describe how the availability of data affects the goals of CRM for each of the individual phases of a customer life cycle, and show how the success of CRM performance relies on the available database.

The next section discusses the impact of customer data on CRM objectives in each of the phases. We provide an overview of the customer data empirically investigated thus far, and discuss their effects along the different phases of the CRM process. The third section provides a summary of the relevance of different types of customer information. Finally, a conclusion is drawn.

## 2 Usage of customer data for empirical research

In order to investigate which specific goals can be reached based on customer data, all of the empirical studies published in leading national and international journals over the past ten years were analyzed. This includes publications in *Zeitschrift für Betriebswirtschaft*, *Schmalenbachs Zeitschrift für Betriebswirtschaftliche Forschung*, *Die Betriebswirtschaft*, *Marketing Zeitschrift für Forschung und Praxis*, as well as those in *Journal of Marketing Research*, *Marketing Science*, *Journal of Marketing*, *Management Science*, *International Journal of Research in Marketing*, *Journal of the Academy of Marketing Science*, *Journal of Interactive Marketing*, and *Business Research*. Other scientific journals have been referenced solely for basic articles. We only considered studies in which customer data could be assigned to individual customers or, on an aggregated level, to individual households. The empirical results are also relevant for business practice because research is subject to similar restrictions as companies: the best-possible results must be attained based on the available data.

As previously mentioned, the scope of customer management depends on the respective phase of the customer life cycle. Therefore, we employ separate tables for each phase of the customer life cycle to present the studies used and customer data analyzed, thereby using the business target variables, i.e. the dependent variables, in the studies as the basis of our analysis. They provide an overview of which customer data can be used to analyze target dimensions in the initiation, expansion, and termination phase.

### 2.1 Initiation phase

The initiation phase of a business mainly focuses on the acquisition of new customers and the reactivation of inactive but profitable customers (Thomas, Blattberg, and Fox 2004). As depicted in *Table 1*, the focus of the studies considered is the analysis of purchase behavior.

It is necessary to predict the *initial purchase* in order to plan the allocation of resources for customer acquisition. Reinartz, Thomas, and Kumar (2005) use various sets of customer information, i.e., basic and purchase data as well as action and reaction data, to forecast the

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Table 1: Empirical findings on the usage of customer data in the relationship initiation phase

Target (dependent) variable	Subgoal		Reference	Data origin			
Operationalization	Control	Analysis		Basic data	Purchase data	Action data	Reaction data
<b>Initial purchase</b>							
Initial purchase probability and rate	✓	✓	Anderson/Simester 2004	✓		✓	
		✓	Sismeiro/Bucklin 2004		✓		✓
	✓	✓	Reinartz/Thomas/Kumar 2005	✓		✓	✓
<b>Clickstream analysis</b>							
Clickthrough probability	✓		Ansari/Mela 2003		✓	✓	
Probability and frequency of visits to the company's website	✓	✓	Park/Fader 2004		✓		
<b>Customer recapture</b>							
Churn/Defection probability		✓	Borle/Singh/Jain 2008, Keaveney/Parthasarathy 2001	✓	✓		
		✓	Jamal/Bucklin 2006	✓	✓		✓
	✓	✓	Ahn/Han/Lee 2006	✓	✓		✓
		✓	Buckinx/Van den Poel 2005	✓	✓	✓	✓
Accuracy of churn forecast		✓	Lemmens/Croux 2006, Neslin et al. 2006	✓	✓		✓
Customer activity status		✓	Fader/Hardie/Lee 2005a, Wübben/von Wangenheim 2008		✓		
		✓	Abe 2009	✓	✓		
	✓	✓	Ahn/Han/Lee 2006		✓		✓
Customer recapture probability		✓	Thomas/Blattberg/Fox 2004		✓		
		✓	Homburg/Hoyer/Stock 2007	✓	✓		



initial purchase probability. The fact that the authors investigate the customer database of a company in the B2B-business explains the high level of data availability; however, initial purchase probabilities and rates can also be predicted with less extensive data. Anderson and Simester (2004) use basic and action data, and Sismeiro and Bucklin (2004) incorporate purchase and reaction data, specifically clickstream data to demonstrate this for B2C-commerce. The action data, i.e. catalogue deliveries, used by Anderson and Simester (2004) allow the analysis of purchase behavior and the control of actions, whereas the study by Sismeiro and Bucklin (2004) exclusively investigates online browsing behavior with respect to the initial purchase probability.

The effect of online promotions can be determined even before the initial purchase with the help of *clickstream analyses*, which also enable predictions for individual customer clickthrough probabilities as well as for visit rates (propensities) of websites (Ansari and Mela 2003; Park and Fader 2004). Interestingly, these results can be derived using surprisingly little information. In the context of the initiation phase, it is also necessary to calculate the allocation of resources for *customer recapture*. To do this effectively, customers with a high risk of defection must first be identified. In contrast to first-acquisition, prediction of customer activity status and churn probability can be determined based on the extensive customer data that is already available, such as the detailed individual purchase histories, as used by Buckinx and Van den Poel (2005). However, the objective of this study is to evaluate the predictive performance of different models rather than the analysis of effect sizes and directions of individual variables. Therefore, the authors only report a complete ranking of the importance of individual predictors instead of the estimated coefficients. A similar approach can be found in Lemmens and Croux (2006), in which different models are used to compare the accuracy of predicting customer churn; the forecast performance is supplemented only by the relative impact of the variables employed.

Determining the status of customer activity status is another target variable related to customer churn; it can be used to assess the extent to which customers are active or inactive (“defected”), e.g., Abe (2009), Fader, Hardie, and Lee (2005a), and Wübben and von Wangenheim (2008) use this approach. The activity status is typically identified based on probability distribution models or associated heuristics which only consider the distribution-based parameters but no exogenous variables. Thus, this study again only indicates which customer data are used to calculate these models.

Analogous to the churn probability (Buckinx and Van den Poel 2005, Lemmens and Croux 2006), a customer recapture probability can be calculated for inactive customers. Thomas, Blattberg, and Fox (2004) and Homburg, Hoyer, and Stock (2007) both demonstrate that,

compared to the prediction of customer defection, the determination of the probability of customer recapture is possible based on less information.

## 2.2 *Expansion phase*

The expansion phase serves to further develop and expand a customer relationship. The extent to which a customer relationship initiated in the first phase has potential to be further developed is revealed in the expansion phase through the frequency and volume of repurchases made, the selection of purchase occasion, and the type and value of products purchased.

In Table 2, the repurchase probability and the purchase frequency (e.g., derived from a customer's purchase history) are shown as relevant target variables for operationalizing a repurchase and, thus, for measuring efficacy and for predicting purchase behavior. The repurchase probability can be found, e.g., in Zhang and Wedel (2009), Moe and Fader (2004) and Van den Poel and Buckinx (2005), whereas Abe (2009), Batistlam, Denizel, and Filiztekin (2007), Fader, Hardie, and Lee (2005a), and Hoppe and Wagner (2007) use the frequency, i.e. the transaction rate, to predict purchase behavior. Repurchase information is highly important, not only for analyzing purchase behavior, but also for managing (direct-) marketing activities, including price promotions (Lewis 2006), coupons (Khan, Lewis, and Singh 2009; Lewis 2004), and internet advertising (Manchanda, Dubé, Goh, and Chintagunta 2006), which are summarized in Table 2 as action data from the studies analyzed. In contrast, participation in loyalty programs (e.g., Bolton, Kannan, and Bramlett 2000) is classified as reaction data.

Additionally, purchase history provides the basis for purchase data, which are used in studies as substantial predictors for repurchase and purchase volume (i.e., sales per customer). The studies addressing purchase volume, such as Ansari, Mela, and Neslin 2008, Borle, Singh, and Jain 2008, and Khan, Lewis, and Singh 2009, incorporate this purchase data in their analyses and also demonstrate that information on the purchase history is highly relevant for the prediction of purchase behavior. Only Mittal and Kamakura (2001) predict repurchase based solely on customer characteristics.

Another important factor in the expansion phase is the question of which of the available sales channels customers use. Empirical studies on *multichannel purchase behavior* show that customer data can be used to make predictions about the type and number of channels customers use (Venkatesan, Kumar, and Ravishanker 2007; Kumar and Venkatesan 2005),

Table 2: Empirical findings on the usage of customer data in the relationship maintenance phase

Target (dependent) variable	Subgoal		Reference	Origin of data			
Operationalization	Control	Analysis		Basic data	Purchase data	Action data	Reaction data
<b>Repurchase</b>							
Repurchase probability and rate		✓	Mittal/Kamakura 2001	✓			
			Zhang/Wedel 2009		✓		
		✓	Van den Poel/Buckinx 2005	✓	✓		
	✓	✓	Lewis 2006, Manchanda et al. 2006		✓	✓	
	✓	✓	Bolton/Kannan/Bramlett 2000, Moe/Fader 2004		✓		✓
	✓	✓	Lewis 2004, Kumar/Shah 2009		✓	✓	✓
	✓	✓	Khan/Lewis/Singh 2009		✓	✓	✓
Frequency of repurchases		✓	Batislam/Denizel/Filiztekin 2007, Fader/Hardie/Lee 2005a, Hoppe/Wagner 2007, Reinartz/Thomas/Bascoul 2008, Reinartz/Thomas/Kumar 2005, Venkatesan/Kumar/Bohling 2007, Wübben/von Wangenheim 2008		✓		
		✓	Abe 2009, Borle/Singh/Jain 2008	✓	✓		
	✓	✓	Liu 2007, Kumar/Shah/Venkatesan 2006		✓		✓
	✓	✓	Venkatesan/Kumar 2004		✓	✓	✓
<b>Purchase volume/quantity</b>							
Sales per customer		✓	Reinartz/Thomas/Bascoul 2008		✓		
		✓	Borle/Singh/Jain 2008, Reinartz/Thomas/Kumar 2005, Venkatesan/Kumar/Bohling 2007	✓	✓		
	✓	✓	Anderson/Simester 2004, Zhang/Krishnamurthi 2004, Zhang/Wedel 2009		✓	✓	
	✓	✓	Liu 2007		✓		✓
	✓	✓	Ansari/Mela/Neslin 2008	✓	✓	✓	✓
<b>Multichannel purchase behavior</b>							
Multichannel adoption time	✓	✓	Venkatesan/Kumar/Ravishanker 2007	✓	✓	✓	
Probability of selection of a distribution channel	✓	✓	Thomas/Sullivan 2005, Ansari/Mela/Neslin 2008	✓	✓	✓	
Numbers of distribution channels	✓	✓	Kumar/Venkatesan 2005	✓	✓	✓	✓
<b>Cross-selling/Up-selling</b>							
Cross-selling probability		✓	Reinartz/Thomas/Bascoul 2008		✓		
		✓	Kamakura et al. 2003, Knott/Hayes/Neslin 2002, Li/Sun/Wilcox 2005, Prins/Verhoef 2007	✓	✓		
Adoption time for cross-selling products	✓	✓	Prins/Verhoef 2007	✓	✓	✓	
Up-selling probability	✓	✓	Bolton/Lemon/Verhoef 2008		✓	✓	

the time to adoption of an additional sales channel (Venkatesan, Kumar, and Ravishanker 2007), and about channel selection (e.g., ordering via catalog versus via Internet) (Thomas and Sullivan 2005, Ansari, Mela, and Neslin 2008).

Furthermore, the expansion stage includes the development of a customer relationship via *cross- and up-selling*. Cross-selling refers to additional company product sales to existing customers, generated with the help of marketing activities (Homburg and Schäfer 2002), whereas up-selling is understood as marketing-induced, repeated sales of the initially purchased product in greater quantities or higher price segments (Müller 2004). Reinartz, Thomas, and Basco (2008) base their investigation of the cross-selling potential of customers or—from the customer’s viewpoint—the probability of cross-buying, solely on purchase data. Kamakura, Wedel, de Rosa, and Mazzone (2003) take information about the purchase history as well as basic data into account, as do Knott, Hayes, and Neslin (2002), Li, Sun, and Wilcox (2005) and Prins and Verhoef (2007). Moreover, Prins and Verhoef (2007) predict the duration until a customer buys a second product that is actively promoted by cross-selling; for this purpose, they use basic, purchase, and the respective action data. Bolton, Lemon, and Verhoef (2008), is the only study to investigate up-selling probability who show for the B2B-area which purchase and action data significantly affect the up-selling probability.

### 2.3 Termination phase

The focus of the termination phase is to identify inactive customers or customers with a high churn potential, and to determine which customers are profitable and unprofitable in order to evaluate whether a customer relationship should be continued or terminated. Table 3 displays empirical studies for individual target variables.

The individual probability of retaining a customer can be used to determine *customer retention* based on basic and action data as developed by Verhoef and Donkers (2005), or on the basis of purchase, action and reaction data found by Verhoef (2003). The study of Drèze and Bonfrer (2008) refers to a similarly extensive data set; the authors predict the customer retention rate with respect to the whole customer base. Moreover, the customer retention probability and rate are often used to measure the effectiveness of marketing strategies so that action data is included in all three studies concerning customer retention.

Although predicting *customer profitability* is important for the whole CRM process (e.g., for targeted customer selection during the acquisition phase or for efficient implementation of marketing strategies during the expansion phase), it is primarily important during the termination phase, where it is the main criterion used to determine whether to continue or terminate a customer relationship.

Table 3: Empirical findings on the usage of customer data in the relationship termination phase

Target (dependent) variable	Subgoals		Reference	Origin of data			
Operationalization	Control	Analysis		Basic data	Purchase data	Action data	Reaction data
<b>Customer retention</b>							
Customer retention probability		✓	Verhoef/Donkers 2005	✓		✓	
	✓	✓	Verhoef 2003		✓	✓	✓
Customer retention rate	✓	✓	Drèze/Bonfrer 2008	✓		✓	✓
<b>Customer profitability</b>							
Customer lifetime		✓	Reinartz/Kumar 2000, Thomas 2001	✓	✓		
	✓	✓	Reinartz/Thomas/Kumar 2005		✓	✓	✓
	✓	✓	Reinartz/Kumar 2003;Reinartz/Thomas/Kumar 2005	✓	✓	✓	✓
	✓		Meyer-Waarden 2007				✓
Customer Share/Share of Wallet		✓	Cooil et al. 2007	✓	✓		
	✓	✓	Leenheer et al. 2007	✓			✓
	✓	✓	Mägi 2003;Meyer-Waarden 2007	✓	✓		✓
	✓	✓	Verhoef 2003		✓	✓	✓
Percentage of profit margin per customer		✓	Bowman/Narayandas 2004		✓		
Mean profit per customer		✓	Homburg/Droll/Totzek 2008		✓		
Mean net value per customer and segment		✓	Reinartz/Krafft 2001		✓		
Customer gross margin as a partial model of CLV		✓	Kumar/Shah/Venkatesan 2006		✓		
	✓	✓	Venkatesan/Kumar 2004	✓	✓	✓	
	✓	✓	Homburg/Steiner/Totzek 2009	✓	✓		✓
	✓	✓	Venkatesan/Kumar/ Bohling 2007, Kumar et al. 2008, Kumar/Shah 2009	✓	✓	✓	✓
Customer life value (CLV)		✓	Fader/Hardie/Lee 2005b, Lewis 2006		✓		
		✓	Jen/Chou/Allenby 2009	✓	✓		
	✓	✓	Reinartz/Thomas/Kumar 2005		✓	✓	✓
Rate/Profit per direct marketing campaign	✓		Reutterer et al. 2006, Simester/Sun/Tsitsiklis 2006		✓	✓	
Profit per direct marketing campaign	✓		Elsner/Krafft/Huchzermeier 2004, Rust/Verhoef 2005	✓	✓	✓	✓
Response to direct marketing	✓		Rust/Verhoef 2005	✓	✓		✓

A major aspect for determining profitability is the *customer lifetime*, used not only for planning, control, and evaluation of marketing activities, but also especially for the estimation of CLV. The strategies of the studies considered differ somewhat. Reinartz and Kumar (2000) and Thomas (2001) predict customer lifetime solely based on basic and purchase data. In contrast, Reinartz and Kumar (2003) use a multitude of variables from all four data categories and analyze these variables with regard to profitable customer lifetime, which is a relevant measure for identifying the performance of marketing activities and for analyzing purchase behavior. Meyer-Waarden (2007) focuses on the control of activities and exclusively investigates the effect of loyalty programs on the duration of a customer relationship using only reaction data.

Furthermore, a number of studies use the Share of Wallet of a customer (or customer share) as a determinant for profitability. Comparing different studies with respect to the data employed reveals that reaction data and information on purchase history are the most relevant types of data for predicting the Share of Wallet. Cooil, Keiningham, Aksoy, and Hsu (2007) determine this target variable based on basic data, i.e. demographic factors such as income and age and situation-related characteristics like expertise and duration of a customer relationship, in addition to using the purchase data. To predict customer share, Leenheer, van Heerde, Bijmolt, and Smidts (2007) also use demographic information such as income, but instead of the purchase history employ reaction data in terms of participation in loyalty programs. Mägi (2003) and Meyer-Waarden (2007) analyze how Share of Wallet is influenced by different basic, purchase, and reaction data-variables. A similar variety of variables can be found in Verhoef (2003), where , reaction and action data is considered in addition to purchase data.

In regards to profitability determination, several other studies can be identified that explicitly use profit-based target variables to measure profitability, such as percentage profit margin per customer (Bowman and Narayandas 2004), average profit per customer (Homburg, Droll, and Totzek 2008), or the mean net value per customer and segment (Reinartz and Krafft 2001). All three studies exclusively use information on the purchase history, showing that profit-related factors can be determined with even a parsimonious set of data.

The most complex target variable for determining customer profitability is the customer lifetime value, which has become increasingly important for customer evaluation in both theory and practice due to its forward-looking approach. Based on the studies investigated, the customer lifetime value, which is conceptually defined as the present value of future Cash Flows (Fader, Hardie, and Lee 2005b), can be determined in different ways. Major challenges include the prediction of future sales and costs, as well as the estimation of the expected customer lifetime.

Due to its complex integration and combination of target variables, the customer lifetime is generally formed by several partial models and can be estimated either consecutively or simultaneously depending on the operationalization. For instance, Kumar, Shah, and Venkatesan (2006), Venkatesan and Kumar (2004) and Venkatesan, Kumar, and Bohling (2007) predict the gross margin per customer and purchase frequency (see also Chapter 2.2, expansion phase) in separate models, and then integrate both dimensions into a customer individual CLV model. In addition to the purchase, action, and reaction data used for gross margin models, they include the quantity of marketing activities and marketing expenses per customer as well as a discount factor to estimate the present customer lifetime value. Kumar, Venkatesan, Bohling, and Beckmann (2008) and Kumar and Shah (2009) use the same CLV concept and also predict the gross margin per customer. However, they estimate purchase probability instead of the purchase frequency (see also Chapter 2.2, expansion phase) and the expected number of marketing contacts per customer. To determine the gross margin, they, like Venkatesan, Kumar, and Bohling (2007), consider variables from all four data categories, in order to be able to draw conclusions on the performance of marketing activities as well as on relevant influences for analyzing customer behavior. Coefficients of demographic- and business-specific variables are not reported because they serve as covariates and are primarily used to analyze the profiles of previously defined customer segments.

Homburg, Steiner, and Totzek (2009) use the gross margin, which represents the present customer value, as the basis for predicting segment-specific CLV. They also consider predictors of basic, purchase, and reaction data to determine customer individual gross margins. Because their focus is to identify the most relevant influencing factors (as in some of the previously mentioned studies), Homburg, Steiner, and Totzek (2009) do not give an overview of the estimated coefficients but rather provide a ranking of the relative importance of the predictors.

Additional approaches for the determination of customer (lifetime) values can be identified. Lewis (2006), for example, predicts individual customer values based on a simple regression model and a few variables of the purchase history. Fader, Hardie, and Lee (2005b) determine the expected numbers of transactions and the future sales per transaction separately by using purchase data which have been already entered into the previously mentioned distribution models. Finally, the authors multiply the results and weight them with a gross margin rate to obtain a customer lifetime value. However, Jen, Chou, and Allenby (2009) simultaneously estimate the time between two purchases (“interpurchase time”) as a measure for purchase frequency and the sales volume based on basic and purchase data in a single model, and derive a customer value based on these results. In contrast to previous studies, the customer value in Jen, Chou, and Allenby (2009) represents the sales volume per time unit rather than

an undiscounted value of future sales. Reinartz, Thomas, and Kumar (2005) identify the drivers for long-term customer profitability based on various purchase, action and reaction data and use a two-step model with which they also estimate the customer-relationship duration (given acquisition) relevant for determining the profitability.

Finally, in this context, it is also relevant to consider studies that investigate the sales volume and profit of direct marketing activities and therefore measure customer profitability indirectly. Although they consider target variables that have been aggregated over customers, they use individual data as influence factors. Simester, Sun, and Tsitsiklis (2006) and Reutterer, Mild, Natter, and Taudes (2006) both use purchase and campaign-relevant action data to predict the turnover of a direct marketing campaign aggregated over all active customers. Elsner, Krafft, and Huchzermeier (2004) analyze the performance of a new direct marketing strategy and used customer individual data from all four categories. Elsner, Krafft, and Huchzermeier (2004), along with Simester, Sun, and Tsitsiklis (2006), use the dynamic optimization of direct mailings as the focus of their investigations, and as such do not present the coefficients of the influence-factors used. Both studies do, however, provide the results of the optimized compared to the original mailing strategies, such as the growth of profit and the increase of active customers. Rust and Verhoef (2005) analyze customer reactions to direct marketing activities based on a variety of predictors of basic, purchase, and reaction data. In a second step, they predict to what extent direct marketing activities can lead to a change in profit.

Up to now, we have shown that the investigation of different target variables is not restricted to certain customer data, and data stemming from various sources may be employed. Whether and to what extent the individual data utilized in the studies affect target variables will be analyzed in the next chapter.

### **3 Relevance of customer data for CRM objectives**

The decision of which customer data might be suitable for analyzing and predicting specific aims is important, as is the examination of which data have proven to be relevant to a particular purpose.

In general, it is inefficient to use all available information for analyses; conversely, omitting important influence factors can lead to biased results and to misjudgment of central correlations. In the following, based on Table 4, we present customer data that significantly influence respective target dimensions. Notably, the customer data identified as significant seems to consist mainly of the same, limited set of information. Moreover, studies are



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Table 4: Relevant customer data based on empirical literature

Target (dependent) variable	Reference	Basic data				Purchase data					Action data		Reaction data	
		Age	Gender	Income/ size turnover	Educational level	Recency	Frequency	Monetary value/ share of wallet	Duration of customer relationship	Cross-buying	Direct-marketing measures	Promotions	Participation in loyalty programs	Customer- initiated contacts
<i>Operationalization</i>														
<b>Clickstream Analysis</b>														
Clickthrough probability	Ansari/Mela 2003					—*					++			
Probability and frequency of visit / Website	Park/Fader 2004					—	+							
<b>Initial purchase</b>														
Initial purchase rate	Anderson/Simester 2004										+			
Initial purchase probability	Sismeiro/Bucklin 2004 Reinartz/Thomas/Kumar 2005			+			n.s.				+		++	+
<b>Customer churn</b>														
Churn/Defection probability	Keaveney/Parthasarathy 2001 Borle/Singh/Jain 2008 Jamal/Bucklin 2006 Ahn/Han/Lee 2006 Buckinx/Van den Poel 2005		n.s.	—	—	+	—	n.s.						
	Lemmens/Croux 2006	n.s.	n.s.					—					+	+
	Fader/Hardie/Lee 2005b		—					+					+	+
Accuracy of churn forecast	Buckinx/Van den Poel 2005		x			x	x	x	x		x		x	
Customer activity status	Lemmens/Croux 2006	x		x			x	x	x					x
	Fader/Hardie/Lee 2005b					x	x							
	Wübben/von Wangenheim 2008					x	x							
	Abe 2009	n.s.	n.s.					+					n.s.	+
	Ahn/Han/Lee 2006							+						
<b>Customer recapture</b>														
Customer recapture probability	Thomas/Blattberg/Fox 2004 Homburg/Hoyer/Stock 2007	+				—			+					
									n.s.					
<b>Repurchase</b>														
Repurchase probability	Mittal/Kamakura 2001	++	++		++									
	Van den Poel/Buckinx 2005	n.s.	++			—*		+						
	Lewis 2006											—*		
	Manchanda et al. 2006						++				++		++	
	Bolton/Kannan/Bramlett 2000						++		n.s.				++	
	Moe/Fader 2004						++							++
	Ansari/Mela/Neslin 2008	n.s.		+		+		n.s.			+		+	
	Kumar/Shah 2009					U	+	+	+	+	+		+	∩
	Lewis 2004					—		+			+		+	
	Khan/Lewis/Singh 2009					++	++	—*			++		++	

Table 4: Relevant customer data based on empirical literature (continued)

Target (dependent) variable	Reference	Basic data				Purchase data				Action data		Reaction data		
Operationalization		Age	Gender	Income/ Size Turnover	Educational level	Recency	Frequency	Monetary Value/ share of wallet	Duration of customer relationship	Cross-buying	Direct-marketing measures	Promotions	Participation in loyalty programs	Customer-initiated contact
Quantity/ Frequency of repurchases, time period between purchases (interpurchase time)	Batislam/Denizel/Filiztekin 2007					x	x		x					
	Fader/Hardie/Lee 2005a					x	x							
	Hoppe/Wagner 2007					x	x							
	Wübben/von Wangenheim 2008					x	x							
	Kumar/Shah/Venkatesan 2006						+		+	+				
	Venkatesan/Kumar/Bohling 2007					-		+		+				
	Abe 2009	n.s.	n.s.					+						
	Borle/Singh/Jain 2008		n.s.			n.s.		+	*					
Liu 2007						+		n.s.				+		
Venkatesan and Kumar 2004					+				+	∩*			+	+/∩* <sup>1</sup>
<b>Purchase volume</b>														
Sales per customer	Reinartz/Thomas/Bascoul 2008									n.s.				
	Borle/Singh/Jain 2008		+			+		n.s.						
	Venkatesan/Kumar/Bohling 2007			+		-		+	+	+				
	Zhang/Krishnamurthi 2004						-	+	+		+			
	Zhang/Wedel/Pieters 2009							+			+			
Quantity of products per customer	Anderson/Simester 2004					*	+	+			n.s.			
Average turnover per product and customer	Anderson/Simester 2004					n.s.	+	+				-*		
	Liu 2007						+		n. s.				+	
	Khan/Lewis/Singh 2009	n.s.				n.s.	+	-*			+		n.s.	
<b>Multichannel purchase behavior</b>														
Adoption time for an additional distribution channel	Venkatesan/Kumar/Ravishanker 2007		-*	n.s.			-*			-*	U*			
Probability catalog vs. Internet	Thomas/Sullivan 2005						-					-		
	Ansari/Mela/Neslin 2008	+				+		n.s.			-			
Numbers of distribution channels	Kumar/Venkatesan 2005			+			+		+	+	+			+

Table 4: Relevant customer data based on empirical literature (continued)

Target (dependent) variable	Reference	Basic data				Purchase data					Action data		Reaction data	
		Age	Gender	Income/ size turnover	Educational level	Recency	Frequency	Monetary value/ share of wallet	Duration of customer relationship	Cross-buying	Direct-marketing strategies	Promotions	Participation in loyalty programs	Customer-initiated contacts
<i>Operationalization</i>														
<b>Cross- /Up-Selling</b>														
Cross-selling probability	Reinartz/Thomas/Bascoul 2008 Kamakura et al. 2003 Li/Sun/Wilcox 2005 Knott/Hayes/Neslin 2002			+	+		+	+	+					
Adoption probability for a new service	Prins/Verhoef 2007	n.s.	n.s.					U *	∩		— *			
Adoption time	Prins/Verhoef 2007	n.s.	—					U *	n.s.					
Up-selling probability	Bolton/Lemon/Verhoef 2008							++ <sup>2</sup>	— *		+			
<b>Customer retention</b>														
Customer retention probability	Verhoef 2003 Drèze/Bonfrer 2008 Verhoef/Donkers 2005	+		+					+		n.s. — / ∩ <sup>3</sup>		+	+
<b>Customer profitability</b>														
Customer lifetime	Reinartz/Kumar 2000 Thomas 2001 Reinartz/Thomas/Kumar 2005	n.s.		+		— *	+		+				+	
	Reinartz/Kumar 2003 Meyer-Waarden 2007	n.s.		+		∩		+		+	+		+	+
Customer Share/Share of Wallet	Cooil et al. 2007 Leenheer et al. 2007 Mägi 2003 Verhoef 2003	n.s.		— *	n.s.				— *				+	
	Bowman/Narayandas 2004 Homburg/Droll/Totzek 2008	n.s.	n.s.	n.s.			— *	n.s.					n.s.	
Percentage of profit per customer								+	n.s.		+		+	
Mean profit per customer								+						
Mean net value per customer and segment	Reinartz/Krafft 2001							+	+ / — / n.s.					
Turnover/Profit (catalog, email, voucher)	Simester/Sun/Tsitsiklis 2006 Reutterer et al. 2006					X	x	x	x		x			
Reaction to direct-mailings	Rust/Verhoef 2005		—	+	+	+	—	+	—		+		+	
Reaction to magazines	Rust/Verhoef 2005		—	+	+	—	+		n.s.				+	

Table 4: Relevant customer data based on empirical literature (continued)

Target (dependent) variable	Reference	Basic data				Potential data					Action data		Reaction data	
		Age	Gender	Income/ size turnover	Educational level	Recency	Frequency	Monetary value/ share of wallet	Duration of customer relationship	Cross-buying	Direct-marketing strategies	Promotions	Participation in loyalty programs	Customer-initiated contacts
Operationalization	Profit of the campaign (Direct mail, journal)	X	x	x	x	x	x	x	x	+	x			x
	Customer gross margin						+		+	+				
	Venkatesan/Kumar 2004			+				+			+	*		
	Homburg/Steiner /Totzek 2009	X	x	x		x	x	x	x	x			x	
	Kumar et al. 2008	X	x	x				+	+	+	+		+	∩
	Kumar/Shah 2009	X	x	x				+	+	+	+		+	∩
	Venkatesan/Kumar/Bohling 2007			+		-		+		+	∩			+
	Fader/Hardie /Lee 2005b					x	x	x						
	Lewis 2006					-	+	+						
	Jen/Chou/Allenby 2009		+			+		+						
Customer life value (CLV)	Reinartz/Thomas/Kumar 2005						∩	+		+	+			+

Legend: + / - = positive/negative and statistically significant correlation; ∩ = positive significant correlation, on a threshold with negative correlation;

U= negative/significant correlation, on a threshold with positive correlation; \* = highly significant ( $p < 0,01$ ); n.s.= no significant correlation between customer data and scope of customer management); <sup>1</sup> = Returns; <sup>2</sup> = Customer Share; <sup>3</sup> = Time since last email.

mentioned that do not incorporate exogenous variables apart from distribution-based parameters and therefore do not designate estimated coefficients. This is due to the methodology used, such as the application of so-called distribution models. Therefore, these studies only provide information about which customer data has been used to calculate these models (marked by “x” in *Table 4*).

### 3.1 Basic data

According to usage frequency, the basic data investigated here, including *age*, *gender* and *income*, seem to be of relatively high importance for the companies’ customer management. However, an analysis of the correlations between customer data and the aims of customer management only sporadically confirms the relevance of this information. A significant, positive influence of age was identified in more than one study analyzing the same target variable with regard to cross-selling and customer retention probability. Gender was significant in two of the analyzed studies concerning repurchase probability and cross-selling; a positive correlation implies that men have a higher repurchase probability or are more susceptible to buying additional products than women. Furthermore, *income* and *educational level*, which are considered in only a few studies, have been proven to be positively relevant for cross-selling probabilities. In addition, income has an important influence on customer profitability. The results demonstrate that higher income is an indicator for a considerably longer customer lifetime and a higher customer gross margin. Moreover, gender, income, and educational level all significantly influence direct marketing actions.

The relevance of basic data concerning cross-selling and direct marketing activities (i.e., activity-related target variables) indicates that this information plays a central role in the selection, design, and control of customized and segment-specific actions. In several empirical studies, these data are used as control variables, covariates or features to characterize the segmentation of the customer base rather than as predictors (Prins and Verhoef 2007).

### 3.2 Purchase data

In contrast to basic data, purchase data, primarily the variables of the *RFM-Model* (*Recency–Frequency–Monetary Value*; compare Fader, Hardie, and Lee 2005b), are used in most of the studies and have a (highly) significant influence on different target strategies of customer management. This suggests that the purchase history, i.e. the time since the last purchase (*Recency*), the purchase frequency (*Frequency*) and the cumulative sales of past purchases (*Monetary Value*), are of major importance for the prediction of customer individual (trans-) actions and performance figures.

Indeed, *recency* proves to be an important predictor for clickstream analysis, repurchase, and purchase volume. Recency has a significant, negative influence on the clickstream probability, which can be interpreted to mean that the probability decreases with increasing length of time since the last visit to the website.

The various directions of the effects found for repurchase may be due to the different kinds of products, such as long-lasting durables (positive correlation) or drugstore products and wine (negative correlation) considered. In other words, both an increase and decrease in purchase probability is plausible, as time since the last purchase increases. Furthermore, recency plays a significant role in terms of customer profitability concerning customer lifetime, reaction to direct marketing actions, and customer lifetime value, although again, with different effects on the target variables described in the previous section.

*Frequency* is an important predictor for the majority of customer management goals. Based on the results attained, a significant negative correlation can be observed with respect to customer defection, a significant, positive effect is demonstrated on repurchase, and a predominantly positive influence on purchase volume is assessed.

Furthermore, a greater purchase frequency expedites the time until adoption of an additional distribution channel, and positively influences the numbers of distribution channels used. Frequency is also an important predictor for the cross-selling probability. The results demonstrate that customers who buy more frequently have a higher cross-selling potential. Finally, purchase frequency, like recency, is highly relevant for most of the target variables related to customer profitability.

The third component of the RFM-model is the *monetary value*, i.e. generally the cumulative sales volume of past purchases, which displays a relevance similar to that of the first two determinants regarding the different aims of customer management. For example, it is of significant importance in terms of customer defection, but no consistent results are determined regarding the churn probability with respect to the direction of effects on the target variables.

However, the influence of monetary value on customer activity status is consistently positive in the investigated studies. Similarly, higher sales volumes of past purchases affect target variables such as “turnover per customer” and “numbers of items per customer” in a positive way, whereas the influence on the repurchase probability is unclear. A predominantly positive correlation is found in the studies, but negative effects can also be demonstrated. This may be explained by the fact that high purchase volumes may indeed represent stock purchases, and thus, the probability of new purchases is generally lower in the periods following such stock purchases.

Furthermore, a high sales volume of past purchases proves to be extraordinarily beneficial for both cross- and up-selling probabilities. A u-shaped correlation was determined between sales volume of past purchases and the time until a (cross-selling initiated) new product or service is adopted. This means that higher sales of past purchases will initially lead to a shortened adoption period, whereas an over-cumulated sales volume will lengthen the period. Based on the results, it is obvious that monetary value is an important predictor for determination of customer profitability as it indicates a significant, positive correlation in terms of most profitability-related target variables.

Information about the *duration of a customer relationship* is also part of the category of purchase data, but it is employed less frequently than the RFM-variables; only two studies have used it to predict the probability of defection and recapture of which one shows that a long-lasting customer relationship has a significantly positive effect on customer recapture. Moreover, other studies concerning repurchase and purchase volume incorporate this variable, in which significant positive, but also insignificant correlations are demonstrated for these respective target variables.

For the cross- and up-selling target variables, the duration of a customer relationship is relevant but the results of different studies also exhibit different directions of effects. Accordingly, the type of influence here is closely related to the respective dependent variable. Similarly, varying directions of effects are also observed when customer relationship duration is considered as a predictor for some partial target variable of customer profitability. This does not apply to the prediction of customer gross margin and lifetime value, where a primarily significant and positive influence of the duration of customer relationship on both of these central target variables could be established.

*Cross-buying* is the last variable of purchase data to be mentioned relevant to this study. This information has only occasionally been considered in the respective analyses, but usually with a significant effect. Cross-buying is of major importance for predicting the frequency of repurchases because the transaction rate is positively affected by the “cross-buying activity.” No consistent direction of effects could be determined with respect to the influence of cross-buying on multichannel-purchases which are analyzed by purchase data as well. Finally, studies have been able to verify the relevance of cross-buying in terms of customer profitability, customer lifetime and customer gross margin. For both target variables, a significant and positive influence from “cross-buying-activity” was identified. Despite the limited numbers of relevant studies, the dominant effect of this variable points to its major importance in addition to the “usual” RFM-variables.

In summary, the consideration of purchase data is essential for many analyses and predictions.

### 3.3 Action data

If action data is available, i.e. the company has information on the effects of direct-marketing activities—for instance, in terms of promotional emails, SMS, catalogs, phone calls or customer-related promotions—this information can be applied to the prediction of clickthrough, initial and repurchase probabilities, as well as customer sales volume. Studies on clickstream analysis, initial purchase, repurchase and purchase volume reveal a significant and positive influence of both direct marketing contacts and the frequency of direct marketing actions on the respective target variable. In the studies considered, customer-related *promotions* (mainly price promotions) affect the repurchase probability negatively. This means that a customer, having initially benefited from a discount has a higher probability of buying only once rather than several times. In another study, promotions are also shown to have a significant, negative effect on customer sales volume. It is notable that promotions have only been investigated in three of the considered studies. However, to the best of our knowledge, there is still little empirical research available with regard to the influence of promotions on the customer individual level in CRM.

Marketing activities are equally relevant for establishing customer profitability, customer lifetime, and customer gross margin. All of the results considered in these studies show a significant positive influence of the frequency of direct marketing contacts on customer profitability in a broader sense. In addition, action data are important in terms of multichannel management analysis and cross- and up-selling. According to the insights gathered from these studies, frequent direct marketing contacts positively influence the numbers of distribution channels used and accelerate the adoption of an additional distribution channel (up to a threshold). The same accelerating effect is observed for the time until a new service (cross-selling) is adopted, but in this case, it is exclusively positive; in other words, a higher frequency always corresponds to a significantly shorter adoption time. Furthermore, the up-selling probability is positively influenced by increased numbers of direct marketing contacts. Overall, the action data considered is highly relevant for the prediction of the target variables of customer management.

### 3.4 Reaction data

In addition to action data, reaction data also play an important role for relevant target variables in the investigated CRM studies. The information on whether a customer participates in a *loyalty program* provides evidence for repurchase probability and customer profitability. The results reveal that loyalty programs promote a long-lasting relationship of a customer with a company, thus positively affecting customer lifetime and increasing the Share of Wallet as well as the customer gross margin. In addition, participation in loyalty



programs is an indicator for a higher response of the participating customer to direct marketing actions, demonstrating a greater involvement with the company.

In addition, the results indicate that an increasing number of *customer-initiated contacts*, such as subscriptions to newsletters and the use of decision support and recommendation systems, have a positive impact on the initial and repurchase probability as well as on customer profitability. In contrast, negative customer-initiated contacts like complaints and returns increase the defection probability of these customers. However, two effects were identified concerning the influence of complaints and returns for repurchase probability and the customer gross margin. While customer-initiated contacts first have a significant, positive impact on repurchase and profitability, the effect may become negative if a certain number of returns is exceeded, resulting in a reduced purchase probability and lower customer gross margin. The former effect can be explained by the fact that customers who buy more frequently also have a higher rate of returns and complaints compared to customers with low purchase activity.

As a conclusion, these studies demonstrate that loyalty programs have a significant and exclusively positive influence on the respective target variables. This also applies to customer-initiated contacts, which have shown to generate significant positive effects in the various studies. Therefore, reaction data—in this case, information about participation in loyalty programs and documentation of different customer-initiated contacts—are of major importance for the predictions of the respective goals of customer management.

#### **4 Conclusion**

Today, automated documentation, along with the ability to inexpensively store customer-related information has shifted the difficulties in the decision-making process away from data availability to data implementation within the framework of CRM systems. Even though a number of empirical studies deal with customer management and implement real consumer data, practitioners are still unable to gauge which data needs to be applied in order to realize CRM objectives. The scope of this paper is to present an overview of the most current state of research in implementing customer data, in order to effectively reach CRM objectives.

The review of the literature shows that, even though target variables are often identical, the data implemented in the studies can be very different. Thus, researchers are confronted with the same problems companies are, namely how to effectively analyze the data available, since different issues and questions surrounding customer management require varying applications and information values of data in order to be solved. To this extent, data that collects active customer participation (purchase, reaction, and action data) has been shown to be better suited for analyses than data merely describing customer characteristics (basic information). Even

though basic information, including age, gender, income, and education levels, is relatively easy to collect and therefore readily available to many companies, the studies presented here mainly use this type of data in order to segment the customer base or as control variables rather than as descriptive variables. Data that includes information about customer behavior elevates the explanatory power of studies in regards to customer management. For example, purchase data, i.e. information regarding purchase times (Recency), purchase frequency (Frequency), and sales volume (Monetary Value), frequently significantly influences the target variables in all phases of the customer life cycle. While purchase data can only be collected for existing customers, action and reaction data can also be gathered for potential customers and interested subjects. Customer information can be utilized for a number of customer management goals, e.g., forecasting customer profitability, as long as companies have access to customer information via either direct marketing actions or customer-initiated contacts.

This study draws two central conclusions. For one, the implication for companies is that data collection and analysis should be conducted dependent upon individual company goals and scopes; the focus of companies should therefore be on collecting quality data rather than focusing on high data volumes. This study provides an overview of which information has been shown to be meaningful for individual aspects of customer management. Second, we clearly show that the collection of purchase, action, and reaction data is more beneficial for customer management due to their higher significance, even though their collection and documentation requires more time and effort. The results of the studies reviewed here show that different goals of customer management can be achieved using different data; some analyses of particular questions come to similar results and implications. On a whole, these findings should enable a simplification of customer management complexities by identifying the core variables necessary to conduct more efficient and cost-effective analyses. This, in turn enables companies to develop and implement appropriate concepts accordingly.

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