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Customer Metrics: The Past, the Present, and the Future in Academia and Practice

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Overview

The need for marketing metrics is intensifying as firms feel increasing pressure to justify their marketing expenditures. One of a company's major marketing investments is in customers, as they are the primary source of revenues and profits.

The objective of this paper is to integrate existing knowledge about customer metrics and provide directions for future research. We define customer metrics very broadly and include both perceptual measures (such as customer satisfaction) and behavioral outcomes (such as customer lifetime value). We use a simple framework to discuss these metrics, whereby a firm's actions (e.g., marketing programs) affect what customers think (i.e., perceptual measures), which in turn influences what customers do (i.e., behavioral outcomes) and what firms get (i.e., financial performance). We discuss each perceptual or behavioral construct and show how it has been measured or modeled, how it links to other constructs, what we know from current research, and what future research is needed. We conclude the paper with four major research challenges that cut across various metrics.

Introduction

Customers are the lifeblood of any organization. Without customers, a firm has no revenues, no profits, and therefore no market value. This simple fact is not lost on most senior executives. In a worldwide survey of 681 senior executives conducted by *The Economist* during October-December 2002, 65% of respondents reported that customers would be their main focus over the next three years, compared to 18% reporting that shareholders would be their main focus (*The Economist Intelligence Unit*). However, even though senior executives realize the importance of customers, they still rely heavily on financial measures, since customer metrics are not clearly defined (Ittner and Larcker 1996).

In this paper, we review and integrate existing knowledge on customer metrics and develop a research agenda that the marketing field must address to move forward in this area. We define customer metrics in the broadest possible way—including perceptual, attitudinal, intentional, and behavioral measures—in an effort to synthesize what is currently known. Current knowledge includes methods developed both in academia and industry, and we assess the strengths and limitations of current research. We also acknowledge that as marketing strives for greater accountability, we need to understand how customer metrics link to costs, profitability, and firm value.

The study of customer metrics extends back many years and incorporates myriad concepts, measures, and models, often ill-defined and overlapping. We will attempt to bring some clarity to them by:

1. Providing a framework for customer metrics that have been used in academia and practice
2. Describing the ways that the constructs underlying the metrics have been defined, measured, or modeled in academic research and in practice
3. Detailing what is currently known about each construct and its relationships with other constructs
4. Proposing a research agenda for the future

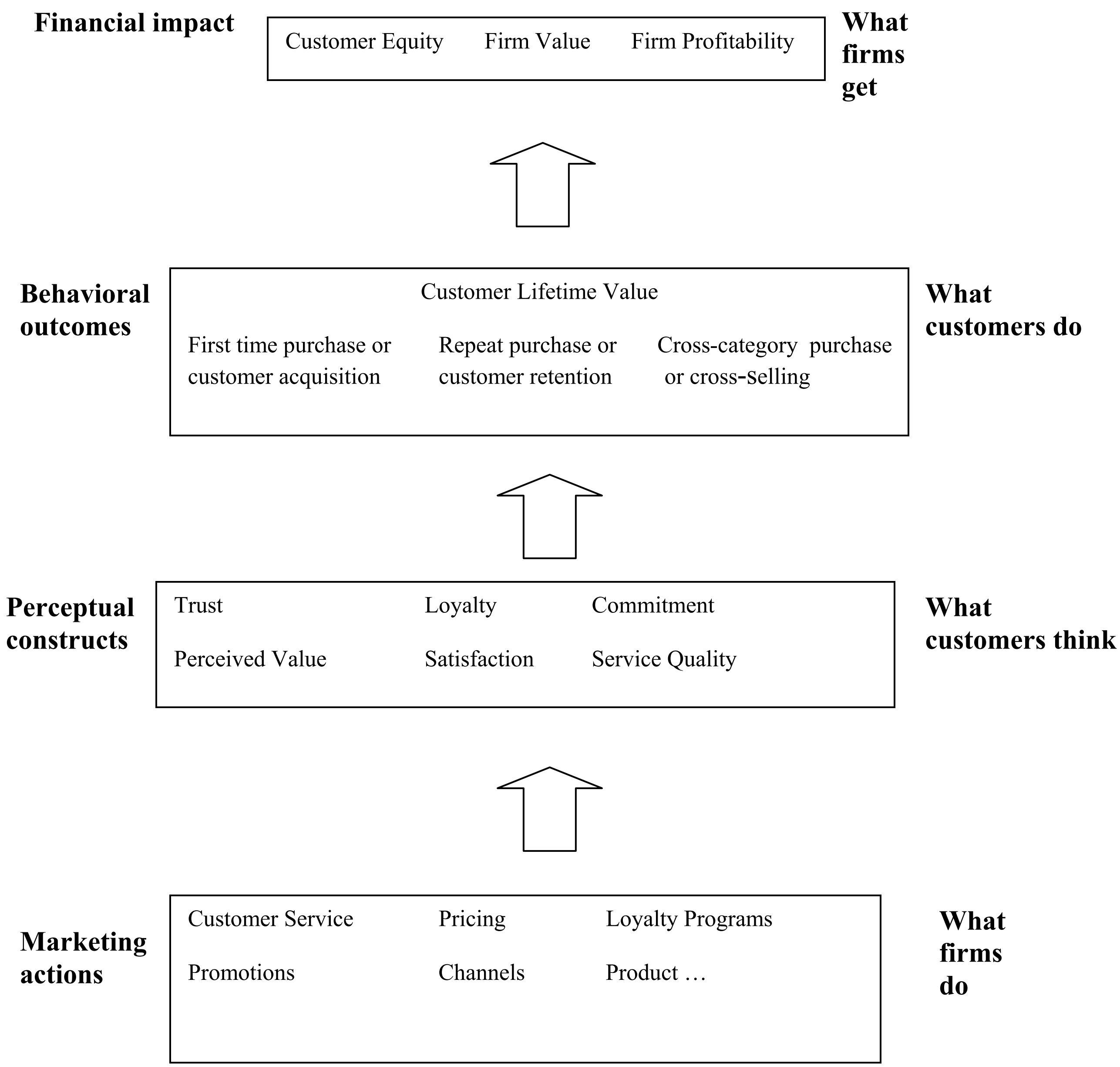
Framework and Organization of the Paper

The term *customer metrics* includes many different types of measurements that have been used in academia and in practice to capture various aspects of customers. They can be broadly categorized into observable and unobservable measures. Observable measures involve behaviors of customers, typically related to purchase or consumption of a product or service. Research dealing with customer acquisition, retention, and lifetime value belongs in this group. Unobservable measures include constructs designed to operationalize perceptions (such as service quality), attitudes (such as customer satisfaction or commitment), or behavioral intentions (such as intention to purchase). The particular metrics used depend upon the purpose of the research and the research orientation of the company or academic.

In this paper, we use a simple framework to describe what companies do (i.e., their marketing actions), what customers think (i.e., unobservable constructs), what customers do (i.e., behavioral outcomes), and how customers' behavior affects a firm's financial performance (i.e., financial outcomes such as profits and firm value) (Figure l).

Clearly, not every research paper necessarily explores each of the boxes suggested in Figure 1. For example, most customer lifetime value studies ignore perceptual and attitudinal measures. Similarly, some studies establish a link between unobservable constructs (e.g., customer satisfaction) and firm value without considering behavioral outcomes or customer lifetime value. Finally, we should emphasize that market and competitor factors are implicit in Figure 1.

Figure 1
A Framework for Customer Metrics



In the next section, we begin our discussion with the unobservable constructs. For each construct, we give its definition, an overview, its measurement issues, and what is known and not known about it. The following section follows a similar structure to discuss the behavioral outcomes. While the focus for unobservable constructs is on measurement, the focus for behavioral outcomes is on modeling. We then highlight broader research issues that cut across these constructs, and conclude in the final section.

Unobservable Constructs and Measures

Research on the concepts "in the black box" is more extensive and has a longer tradition than does research on the metrics outside the black box. These unobservable constructs have enjoyed widespread use for many reasons. First, because they are collected almost exclusively through surveys, they have been relatively easy to obtain and share. Methodologies and best practices were developed both in companies and in marketing-research organizations that spread their use. During the 1990s, for example, all of the major marketing-research suppliers had units or practices in customer satisfaction, and the American Marketing Association sponsored an annual Customer Satisfaction Congress that often drew close to 1,000 registrants from companies. Second, using the metrics as dependent variables allowed companies to diagnose the key attribute drivers that could then be addressed by specific marketing and operational strategies within a company. Third, the measures helped companies track performance over time, benchmark against competitors' offerings, and compare performance across different parts of an organization (e.g., branches, units, territories, countries).

The implicit assumption in the use of these measures is that they are precursors or predictors of observable behavior such as retention, increased consumption, or willingness to pay a premium. These assumptions held even though research linking them to actual behavior is a relatively recent phenomenon. In the 1990s, companies began to question whether the relationship between customer satisfaction (the most frequently measured perceptual concept) and observable behavior was sufficiently strong to justify its use as the primary predictor. Part of their doubt arose from the observation that satisfied customers defect (Jones and Sasser 1995), leading them to question whether a more rigorous goal such as attitudinal loyalty should be the focus of company measurement. Additionally, as database management and customer relationship management have evolved, some companies have found it possible to investigate the relationship between customer satisfaction and observable behavior and have found that it is not as strong as they expected.

Of all the unobservable metrics capturing unobservable constructs, customer satisfaction has been the most widely used because it is generic and can be universally gauged for all products and services, including nonprofit and public services. Even without a precise definition of the term, customer satisfaction is clearly understood by respondents, and its meaning is easy to communicate to managers. Other measures such as service quality, perceived value, and loyalty have also had widespread use in companies and been examined extensively in academic research. Service quality has been measured since the mid-1980s but obviously is limited to examining the intangible aspects of an offering. To a far lesser extent, constructs like commitment and trust have made their way into companies' measurement systems and academic research.

In this section, we critically examine the constructs and that have been used both by academics and practitioners in research.

Customer satisfaction

Definition and Overview. Customer satisfaction has been defined as "the consumer's fulfillment response . . . a judgment that a product or service feature, or the product or service itself, provides a pleasurable level of consumption-related fulfillment" (Oliver 1997). Research has typically portrayed the evaluation of customer satisfaction as disconfirmation of expectations (see Oliver 1997 or Yi 1990 for a full review). This view holds that a consumer compares what is received with a preconsumption standard or expectation.

One of the pivotal definitional issues in the literature is whether satisfaction is best conceived as a transaction-based evaluation or as an overall, cumulative evaluation similar to attitude. Traditionally, satisfaction has been viewed as transaction-specific, an immediate post-purchase evaluative judgment or affective reaction (Oliver 1993). Reflecting the other perspective, Anderson, Fornell, and Lehmann (1994, p. 54) defined as an "overall evaluation based on the total purchase and consumption experience with a good or service over time." Research and practice have operationalized the construct both ways.

More recently, Fournier and Mick (1999) have expanded the dominant paradigm of confirmation/disconfirmation and developed a more holistic view of satisfaction that depends on context, emotions, and meanings embedded in sociocultural settings. One of the major differences between their view and the traditional perspective is that in their view, satisfaction is a dynamic process where the standards of comparison change over time, rather than remaining fixed.

Measurement. Both in practice and in academic research, customer satisfaction has been measured at the transaction level (as in trailer or event-triggered surveys) and at the overall level (as in the American Customer Satisfaction Index). In early studies, academics often focused on measuring confirmation/disconfirmation and expectations, and the nature and type of expectations varied considerably from predictive expectations (Oliver 1997; Tse and Wilton 1988) to desires (Westbrook and Reilly 1983) to experience-based norms (Cadotte, Woodruff, and Jenkins 1987). Applied marketing research tends to measure satisfaction both ways—at the transaction level and, more frequently, as an overall evaluation, a cumulative construct that is developed through all the experiences a customer has with a firm.

What We Know. Customer satisfaction is the most researched customer metric, with more than 150 empirical studies and 350 publications dealing with the topic. Several comprehensive reviews of the research exist (Yi 1990; Oliver 1997; Szymanski and Henard 2001). Most of the academic research deals with the antecedents of customer satisfaction and with modeling customer satisfaction as the disconfirmation of expectations.

Szymanski and Henard (2001), in a meta-analysis using empirical studies that specified customer satisfaction as a measured variable in empirical models, concluded that research findings on antecedents and outcomes of customer satisfaction "vary considerably in statistical significance, direction and magnitude" (p. 16). After examining the most frequently studied antecedents (expectations, performance, equity, disconfirmation of expectations, and affect), they concluded that equity (mean correlation = .50) and disconfirmation of expectations (mean correlation = .46) are most strongly related to customer satisfaction. Despite the definitional importance of expectations in customer satisfaction, the empirical relationship between expectations and customer satisfaction was found to be statistically significant on average (mean r = .27) but mixed and certainly of lower significance than the effects of equity or disconfirmation of expectations. At the time of their analysis, they found that far less attention in the academic literature was devoted to outcomes (such as complaining, negative word of mouth, and repeat purchase) than to antecedents. The researchers also found that moderators of the relationships—including comparison standard, measurement level, method type, participants, and type of offering—in satisfaction models were also statistically significant.

More recent research, often using the American Customer Satisfaction Index (ACSI), has examined the link between customer satisfaction and financial measures using CompuStat and other databases. For example, Gruca and Rego (2003) found that customer satisfaction creates shareholder value by significantly increasing cash flows and reducing cash flow variability. Using data from 1994–2000, they calculated that a 1% increase in customer satisfaction generated over 7% in a firm's future net operational cash flow and a decrease of 4% in its cash flow variability.

What We Don't Know. Given the widespread use of customer satisfaction as a company metric and the large number of academic studies conducted on the topic, surprisingly little empirical evidence exists about the relationships among customer satisfaction, retention, and firm performance. While some studies have found a link between satisfaction and retention (such as Rust and Zahorik 1993), others have questioned this link (Jones and Sasser 1995). For example, Jones and Sasser (1995) suggested that only the "completely satisfied" customers are loyal while the "merely satisfied" customers can easily defect.

Is the relationship between satisfaction and performance linear or nonlinear? Yeung, Ging, and Ennew (2002), correlating data from the American Customer Satisfaction Index and CompuStat, tested different function forms in a regression of profitability on satisfaction. They found that over the observed range of satisfaction scores, the assumption of a linear relationship was acceptable. However, they assumed that the impact of satisfaction on firm profitability was contemporaneous, which may not be an appropriate assumption. Other research has demonstrated a nonlinear relationship between satisfaction and behavioral intentions (Anderson and Mittal 2000; Schneider and Bowen 1999; Taylor 1997). Fullerton and Taylor (2002) found support for a U-shaped relationship between satisfaction and three aspects of loyalty (customer retention/advocacy/willingness to pay more). However, the significant nonlinear effect made only a marginal contribution to the proportion of variance explained in the dependent variables.

When companies began to view customer satisfaction as an insufficiently rigorous measure, some industry experts suggested that *customer delight*, and not customer satisfaction, is the key to customer retention. Xerox, for example, discovered that "totally satisfied" customers were six times more likely to repurchase than those who were simply "satisfied." Other research on customer delight has found that "tremendously satisfied" or "delighted" customers are much more likely to remain customers that those who were just "satisfied" (Jones and Sasser 1995; Oliver, Rust, and Varki 1997; Schneider and Bowen 1999). However, more research is needed to examine whether customer delight is indeed a different construct than customer satisfaction and whether it has a greater impact on retention.

Service quality

Definition and Overview. Perceived service quality is the degree and direction of discrepancy between customers' service perceptions and expectations (Gronroos 1982; Lehtinen and Lehtinen 1982; Lewis and Booms 1983; Sasser, Olsen, and Wyckoff 1978; Zeithaml and Parasuraman 2004). While multiple interpretations of expectations have emerged in research, the notion that service quality is a comparative process is one of the most basic in the field. The second fundamental is that the construct of service quality is made up of five factors or dimensions: reliability, responsiveness, assurance, empathy, and tangibles (Zeithaml and Parasuraman 2004).

Measurement. The dominant measurement approach for quantitative assessment of service quality is SERVQUAL, a multiple-item measure first developed in the 1980s, then tested and refined throughout the 1990s (see a review in Zeithaml and Parasuraman 2004). Researchers first operationalized the service quality gap as the difference between two scores—customer expectations of service quality and customer perceptions of actual service performance—for each of the five dimensions (and associated attributes), for the perceptual attributes that focus-group respondents indicated were critical. Through this early research, the five dimensions of service quality were derived as factors. Refinement and assessment of SERVQUAL over a nearly 20-year period indicate that it is a robust measure of perceived service quality. However, concerns about SERVQUAL have been raised and debated, including the interpretation of and need to measure expectations, the appropriateness of measuring service quality using difference scores, and the generalizability of the five dimensions across all service contexts.

What We Know. SERVQUAL is not a panacea for all service-quality measurement problems, nor should it be used by companies as the sole basis for assessing service quality. Rather, it should be viewed as a component of a more comprehensive service-quality information system. The skeleton, when necessary, can be adapted or supplemented to fit the characteristics or specific research needs of a particular organization. SERVQUAL is most valuable when it is used periodically to track service-quality trends and when it is used in conjunction with other forms of service-quality measurement.

In research exploring the relative importance of service dimensions to overall service quality or customer satisfaction, the bulk of the findings confirms that reliability is most critical (Parasuraman, Zeithaml, and Berry 1988; Boulding et al. 1993; Zeithaml, Berry, and Parasuraman 1996), although others have demonstrated the importance of customization (Fornell et al. 1996) and other factors.

What We Don't Know. Zeithaml and Parasuraman (2004) have detailed the measurement and research issues that remain to be studied on the topic of service quality. We will mention just a few of the key points here.

While the measurement of traditional service quality is in a mature stage, measurement of online service quality is relatively new. Scales to measure online service quality are now being developed (Loiacono, Watson, and Goodhue 2000; Wolfinbarger and Gilly 2002; Zeithaml, Parasuraman, and Malhotra 2000) but need refinement and testing. All scales currently under development—including WebQual, .comQ/eTailQ, and e-SERVQUAL—should be examined for their psychometric properties and diagnostic value and improved where needed. When concepts and measures of e-service quality have been developed, it will be possible to investigate questions about the importance of different dimensions and perceptual attributes to overall e-service quality and its consequences. One issue that needs to be studied is the relative impact of traditional-service and e-service quality on customers touched by both. A key managerial research need is a measurement scale that can be used to capture service quality in both online and offline channels for the same company. Given the differences between service quality and e-service quality, this may be difficult, but it would be valuable for managers to be able to compare online and offline service quality.

Perceived value

Definition and Overview. Perceived value is the most ambiguous and idiosyncratic customer metric. In a general sense, it can be defined as the consumer's objective assessment of the utility of a brand based on perceptions of what is given up for what is received (Zeithaml 1988). Benefits include the intrinsic and extrinsic utility provided by the product or the relationship, and costs include monetary and nonmonetary sacrifices (e.g., time and effort) that are needed to purchase the offering or maintain the relationship. In an exploratory study of the meaning of value to consumers, Zeithaml (1988) identified that the difficulty in definition arises because customers express at least four different definitions of value: (1) value is low price; (2) value is the quality received for the price paid; (3) value is everything obtained from an offering compared to everything given; and (4) value is whatever is desired in an offering. Woodruff (1997) echoed the ambiguity of value in noting that definitions (such as those provided by Anderson, Jain, and Chintagunta 1993; Monroe 1990; and Butz and Goodstein 1996) are often constructed in terms such as utility, worth, benefits, and quality that are themselves ill defined. Houston and Gassenheimer (1987) illustrated another source of ambiguity by claiming that value is personal to each individual, extrinsic or intrinsic, and related either to benefits deriving from use, to potential for use, or to potential for exchange.

Some researchers have attempted to be more precise about value by providing categories or types. For example, Burns (1993) delineated how four different types of value (product value, value in use, possession value, and overall value) affect a customer's evaluation process. Sheth, Newman, and Gross (1991) described five different categories of value that products could provide: functional, social, emotional, epistemic, and conditional. In possibly the most extensive framework, Holbrook (1994) developed a 2 (extrinsic versus intrinsic) x 2 (self-oriented versus other-oriented) x 2 (active versus reactive) classification that results in eight different types of value (efficiency, excellence, status, esteem, play, aesthetics, ethics, and spirituality). When researchers and scholars attempt to develop a definition that incorporates all possible elements that create customer value, they end up with definitions that are so broad as to lack usefulness as metrics, such as the one that Woodruff (1997) specified after careful review of the literature.

Customer value is a customer's perceived preference for and evaluation of those product attributes, attribute performances, and consequences arising from use that facilitate (or block) achieving the customer's goals and purposes in use situations. (Woodruff 1997, p. 142).

Measurement. Because of the ambiguity of the definition of customer value, the construct is virtually impossible to measure with validity, reliability, and consistency. In many academic and company studies, perceived value has been measured with a single item or a small number of items (Bolton and Drew 1991; Grisaffe and Kumar 1998). The single-item measures typically lack validity. For example, Grisaffe and Kumar (1998) measured absolute value with a single item: "Considering the client's overall quality in relation to your cost, how would you rate the client's value for the money?" This item reflects just one of many possible meanings of value to customers, and it incorporates only quality and value as components. However, an item that does not define perceived value at all, instead just asking customers to rate "the perceived value of XYZ offering," suffers from validity problems as well, as respondents can then interpret value in their own idiosyncratic ways; for example, some would be incorporating price in their answers and others would not.

Some researchers have included multiple items in their scales to reflect the different meanings of perceived value. One perceptual scale that captures multiple meanings and possesses good internal consistency and reliability was created by Sirdeshmukh, Singh, and Sabol (2002). The scale (coefficient alpha = .92) used four items: one to capture the perceived deal, one to reflect whether the time spent to travel to the site is reasonable, one to reflect the worth of the effort expended, and one to reflect the overall experience. Other attempts to capture the multiple perceptual meanings of value in the construct have been less successful in creating internally consistent indicators.

Modeling the construct is another approach. Kamakura and Russell (1989) developed a model using the bundle of tangible and intangible values as elements, weighted the values by importance for individual purchasers, and created unique value equations for each purchaser in different categories. While this approach captures the variety of individual customers' meanings of perceived value and is useful for modeling preference, it is too complex and cumbersome to be useful as a customer metric.

What We Know. Beyond showing that value is a desirable customer outcome, most attempts to investigate and measure value have not yielded useful data. Woodruff (1997) commented: "The growing body of conceptual knowledge about customer value is quite fragmented, with different points of view advocated and no widely accepted way of pulling all these views together" (p. 142). The number of research studies that have investigated the topic is considerably smaller than the number of studies on customer satisfaction, commitment, and service quality. We believe that this is due to the difficulty in defining value in any way that can be translated into valid metrics. Perceived value is a high-level abstraction, and to fully represent all its components, multiple other high-level abstractions and specific attributes like price are required. Little of what has been researched can be meaningfully synthesized because each study either interprets and measures value in widely different ways or operationalizes it as a single item, leaving the researcher without a full understanding of how the customer is interpreting it. Researching perceived value is like studying other high-level abstractions such as happiness or love, terms that academics in fields relating to them have found equally difficult to describe and delineate.

What We Don't Know. While there is some empirical evidence that value is important in customer decisions (Sirdeshmukh, Singh, and Sabol 2002; Grisaffe and Kumar 1998; Gardial et al. 1994), we believe that the difficulty of clearly defining and measuring perceived value limits its use as a customer metric, although modeling preferences and value has obvious applications in marketing for other reasons, such as identifying the attributes to build into products and services.

For purposes other than customer metrics, Woodruff (1997) proposed an integrative, multistep approach to uncovering what customers value in a firm's offering. Despite the richness and potential of this approach, it still does not provide us with greater potential for the measurement of customer perceptions of value, as it suggests that a company should broaden the multiple sources and types of information used to assess customer perceptions of value before, during, and after purchase.

Trust

Definition and Overview. Trust has been proposed as a major determinant of relational commitment and loyalty. Moorman, Deshpande, and Zaltman (1993, p. 82) defined trust as "a willingness to rely on an exchange partner in whom one has confidence" and viewed it as a result of the ability to perform (expertise), reliability, and intentionality. Morgan and Hunt (1994, p. 23) defined it as the perception of "confidence in the exchange partner's reliability and integrity." Most recently, Sirdeshmukh, Singh, and Sabol (2002) defined it as the "expectations held by the consumer that the service provider is dependable and can be relied on to deliver on its promises" (p. 17). Trust has been studied in the context of social exchange, organizational behavior, and communications.

Measurement. Most measures of trust in the marketing literature have been created for a specific study and are not generalizable. For example, Sirdeshmukh, Singh, and Sabol (2002) created two 4-item scales (one related to employees of a store and the other related to the store itself), each with coefficient alphas of .96. Similarly, Garbarino and Johnson (1999) proposed a 4-item scale to measure the trust that attendees at a theater company had about performances at the theater (coefficient alpha = .73). In the most systematic, theory-based, and generalizable scale, Morgan and Hunt (1994) developed a 7-item interorganization trust scale (coefficient alpha = .947) adapted from Meyer and Allen (1984).

What We Know. Studies have demonstrated that trust is an essential element in building strong customer relationships and sustainable market share (Gundlach and Murphy 1993; Nooteboom, Berger, and Noorderhaven 1997; Garbarino and Johnson 1999; Tax, Brown and Chandrashekaran 1998). Despite the fact that trust has been studied in a variety of business-to-consumer and business-to-business contexts, trust may only be important for customers with a collaborative orientation (Anderson and Narus 1991)—customers who are partnering with their suppliers. Supporting this perspective, in a study of two consumer service industries (clothing purchases and nonbusiness airline travel), Sirdeshmukh, Singh, and Sabol (2002) found that value, rather than trust, emerged as the consistent, significant, and dominant determinant of customer loyalty, regardless of the service category. They conclude that consumers' evaluation of value in relational exchanges carries greater weight in loyalty judgments than trust.

Satisfaction, trust, and commitment play different roles in the prediction of future intentions for low and high relational customers (Garbarino and Johnson 1999). Trust and commitment are the mediators with high relational customers, and customer satisfaction is the mediator with low relational customers. This means that for partnerships with suppliers, and in business-to-business relationships in general, trust and commitment may be more important to measure than satisfaction.

What We Don't Know. Although some companies are using trust as a metric, it is unclear whether trust is a means to loyalty or a metric worth measuring in its own right. One of the most important things we need to understand is in what types of relationships trust, rather than customer satisfaction, should be the focus of measurement and improvement. Trust is not relevant for all types of interactions or customer relationships, as shown in Garbarino and Johnson (1999). Firms may need to practice both transactional and relational marketing with different groups of customers and identify the groups that are relevant for each focus.

A question many companies are trying to answer is whether companies can build trust and commitment in customers with weak bonds. What, if any, marketing programs are effective and efficient to achieve this goal?

Commitment

Definition and Overview. Moorman, Zaltman, and Deshpande (1992, p. 316) defined commitment as "an enduring desire to maintain a valued relationship." Others have defined it as "an implicit or explicit pledge of relational continuity between exchange partners" (Dwyer, Schurr, and Oh 1987, p. 19) or as "psychological attachment" to an organization (Gruen, Summers, and Acito 2000, p. 37). Morgan and Hunt (1994) argued that commitment is "an exchange partner believing that an ongoing relationship with another partner is so important as to warrant maximum efforts at maintaining it" (p. 23).

Research in social psychology, marriage, and organizational behavior has provided the definitional/theoretical foundation for commitment (see Morgan and Hunt 1994 for a description of these roots). In the most directly relevant literature, that on organizational behavior, relationship commitment is one of the oldest and most researched variables. Meyer and Herscovitch (2001), in a major review of the workplace commitment literature, found that most research support has been established for three dimensions of commitment: affective, continuance, and normative. Originally conceived by Meyer and Allen (1984), these dimensions were concluded by Meyer and Herscovitch to be appropriate regardless of the target of commitment. Bansal, Irving, and Taylor (2004) applied this to marketing by viewing the affective component as binding the consumer to the service provider out of desire, the normative component out of perceived obligation, and the continuance component out of need. They found support for the fact that commitment can be desire-based ("I want to stay"), cost-based (I ought to stay), or obligation-based ("I have to stay"). Gruen, Summers, And Acito (2000), using this three-component structure of commitment in a membership relationship context (a national association of insurers), demonstrated that the components had differential effects on desired dependent variables such as coproduction and member participation.

Researchers have viewed commitment as comprising other components. Gundlach, Achrol, and Mentzer (1995) identify three components: an instrumental component of some form of investment, an attitudinal component that is either affective commitment or psychological attachment, and a temporal dimension indicating that the relationship exists over time. Bolton, Lemon, and Verhoef (2004) use only two categories: affective (desire to maintain a relationship based on feelings of loyalty and affiliation) and calculative (derived from economic motives). Brown, Lusch, and Nicholson (1995) examined normative commitment, based on identification and involvement with an organization, and instrumental commitment, based on compliance in the hope of achieving a favorable reaction from another organization.

Commitment has been studied in both business-to-business contexts (Gruen, Summers, and Acito 2000; Morgan and Hunt 1994) and consumer contexts (Verhoef, Franses, and Hoekstra 2002). Commitment has also been studied in the context of relational ties among channel members (Brown, Lusch, and Nicholson 1995; Kim and Frazier 1997; Kumar, Sheer, and Steenkamp 1995).

Measurement. Inconsistent conceptualizations, particularly among components of commitment, have led to many different ways of measuring the concept. In most academic studies on commitment, researchers have in one way or another modified the scales of employee commitment to an organization to measure the construct of consumer commitment, e.g., to a health club (Kelley and Davis 1994) or to a grocery store (Bettencourt 1997).

Many researchers in marketing have viewed commitment as a unidimensional concept and measured it that way (Bettencourt 1997; Garbarino and Johnson 1999; Hennig-Thurau, Gwinner, and Gremler 2002; MacKenzie, Podsakoff, and Ahearne 1998; Morgan and Hunt 1994; Pritchard, Havitz, and Howard 1999; Sharma and Patterson 2000; White and Schneider 2000). For example, Morgan and Hunt (1994) adapted items from the organizational commitment scales of Meyer and Allen (1984) and Mowday, Steers, and Porter (1979) to create a 7-item unidimensional scale (coefficient alpha = .895).

Researchers in organizational behavior, in contrast, have developed richer and multidimensional conceptualizations. The literature on employee commitment measures such facets as personal identification with the organization, psychological attachment, concern for the future welfare of the organization, and loyalty. Some research in marketing has built upon this organizational literature, measuring and examining the different components of commitment. Gruen, Summers, and Acito (2000) and Bansal, Irving, and Taylor (2004) developed a three-dimensional measure including affective, normative, and continuance components.

What We Know. As it has been conceptualized in marketing and other fields, commitment represents the strongest level of attachment to an organization. For this reason, it has been most frequently studied in organizations and contexts where the potential for development of strong relationships is maximized: longterm business-to-business relationships and channel situations. Just as human beings have a variety of relationships with the people around them—strong relationships with family and close friends and weaker ties to acquaintances or other associates—customers feel strong allegiances with some organizations and weaker allegiances with others. With few exceptions, commitment has not been found to be important in other than business-to-business contexts. For example, even in a membership relationship, where customers have longstanding ties with an organization, Gruen, Summers, and Acito (2000) found that core service performance had a direct relationship with retention and was not mediated by any of three forms of commitment.

Research in other fields, and a handful of studies in marketing, indicate that commitment has several different components: an affective component that reflects the feeling of attachment, a continuance component that captures the economic benefits that accrue to a customer in a longterm relationship, and a normative component. Differentiating the components adds to the explanatory power of the construct, as some components have been found to be important in some contexts and not in others. The two components that seem to be most relevant and generalizable to marketing organizations are the affective component and the continuance or calculative components. The normative component ("I should belong to this organization" or "I should stay with this organization") is likely to be less widely applicable.

What We Don't Know. While commitment appears to be a useful metric in capturing customer allegiance in a business-to-business context, its applicability to business-to-consumer contexts has not been established. Although creating commitment in customers is desirable, it may simply not be possible in many industries. Banks, for example, are currently attempting to forge strong relationships with their customers and are interested in measuring (and developing) strong affinity, yet they have found that in most bank contexts this is difficult to achieve because customers perceive banks as commodities. Is it possible for customers to feel committed to banks where all they do is their checking, particularly if they accomplish this online or through teller machines? On the other hand, can customers feel a strong sense of commitment to other services that a bank can offer, particularly when there is an individual (such as a financial planner or broker) who helps them arrange their savings and investing goals? Are there some industries, particularly service industries, where frequency of contact might lead to strong affect and thus commitment?

Is there any relationship between brand loyalty and commitment? In other words, if customers are brand-loyal to Coke or to Harley-Davidson motorcycles, can they be viewed as committed to the brand or organization? What is the overlap between brand loyalty and commitment in these contexts, and is it useful to measure commitment when brand-loyalty metrics are already in place?

Do the different components of commitment differentially affect spending, retention, and other outcomes to the firm? Limited research has shown that different types of commitment lead to different outcomes in a membership organization (Gruen, Summers, and Acito 2000), yet no component of commitment has been significantly related to retention. Bolton, Lemon, and Verhoef (2004) suggest that affective commitment should be especially strong in service industries that provide hedonic experiences, but there is not enough research yet to conclude that this is true.

Loyalty

Definition and Overview. Behaviorally, consumers can be defined as loyal if they repeatedly buy a product over some period of time. Jacoby, Chestnut and Fisher (1978), however, took exception to this simple definition and were the first researchers to view loyalty psychologically rather than behaviorally. They recognized that behavioral loyalty could be spurious because it could be based on convenience or switching costs rather than true loyalty. It could also be misleading if consumers were multibrand loyal. In a representative definition that combines both the behavioral and attitudinal perspectives, Oliver (1997, p. 392) defines loyalty as “a deeply held commitment to rebuy or repatronize a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior.” Consumer loyalty is indicated by an intention to perform a diverse set of behaviors that signal a motivation to maintain a relationship with the focal firm, including allocating a higher share of the category wallet to the specific service provider, engaging in positive word of mouth, and repeat purchasing (Zeithaml, Berry, and Parasuraman 1996).

Measurement. Loyalty has been measured both behaviorally as repeat-purchase frequency or relative volume of purchasing (Tellis 1988) and attitudinally as repurchase intentions (e.g., Reynolds and Arnold 2000), intention to recommend to others (e.g., Mattila 2001), likelihood of switching (e.g., Hennig-Thurau, Gwinner, and Gremler 2002), or likelihood of buying more (e.g., Selnes and Gonhaug 2000). Zeithaml, Berry, and Parasuraman (1996) combined these different aspects of loyalty and developed a behavioral-intentions battery with four dimensions—loyalty, propensity to switch, willingness to pay more, and external response to service problems—composed of 14 specific behavioral intentions likely to result from perceived service quality.

In a departure from the type of rigor that academic researchers have used in capturing the construct of loyalty, Reichheld (2003) recently claimed that complex measurements are not needed—that the only number a company needs is an indication of whether customers will recommend the firm to others.

What We Know. What we know about loyalty is dependent upon the aspect of loyalty on which we focus. For example, if we focus on intentions to purchase, company data indicate that positive experiences lead to loyalty. Toyota found that intent to repurchase a Toyota automobile increased from a base of 37% to 45% with a positive sales experience, from 37% to 79% with a positive service experience, and from 37% to 91% with both a positive sales experience and a positive service experience (McLaughlin 1993).

Gale (1992) assessed the relationship between level of service quality and willingness to purchase at AT&T. Of AT&T's customers who rated the company's overall quality as excellent, over 90% expressed willingness to purchase from AT&T again. For customers rating the service as good, fair, or poor, the percentages decreased to 60%, 17%, and 0% respectively. According to these data, willingness to repurchase increased at a steeper rate (by 43%) as the service-quality rating improved from fair to good than when it went from poor to fair (17%) or from good to excellent (30%). These results suggest that the impact of service quality on willingness to repurchase is most pronounced at some intermediate level of service quality.

What We Don't Know. Oliver (1999) notes that the relationship between customer satisfaction and loyalty is asymmetric: "Although loyal customers are typically satisfied, satisfaction does not universally translate into loyalty" (p. 33). He concludes that satisfaction is a necessary step in loyalty formation but that other factors, including personal determinism and social bonding at the institutional and personal level, are necessary for loyalty. He further indicates that some organizations should not pursue customer loyalty because of the nature of the product category or consumer disinterest. For these organizations, satisfaction is the only feasible goal.

Behavioral Outcomes

In this section, we discuss behavioral outcome metrics such as customer lifetime value, customer acquisition, customer retention, and cross-selling. We describe how they are modeled, the relationships among various constructs (both behavioral and perceptual), what is known, and what requires further investigation.

Customer lifetime value

Definition and Overview. Customer lifetime value (CLV) is the present value of all future profits obtained from a customer over the life of his or her relationship with a firm. This concept is similar to the discounted-cash-flow approach used in finance, except for two key differences. First, CLV is defined at an individual-customer or segment level, since it recognizes that some customers are more important and profitable than others. Second, CLV explicitly incorporates the possibility of a customer defecting to competitors in the future.

Modeling. By definition, CLV is (for simplicity we are omitting consumer subscript)

$$CLV = \sum_{t=0}^{T} \frac{(p_t - c_t) r_t}{(1+i)^t} \tag{1}$$

where p_t = price paid by a consumer at time t,
c_t = direct cost of servicing the customer at time t,
r_t = probability of customer buying from the firm at time t,
i = discount rate or cost of capital for the firm,
T = time horizon for estimating CLV.

It is common for researchers to build separate models for future contribution margin ($p_t - c_t$) and probability of repeat buying or being "alive" in the future (r_t) and then combine them to estimate CLV. Most studies have either used average contribution margin based on past purchase data (Reinartz and Kumar 2000; Gupta, Lehmann, and Stuart 2004) or a Tobit model to predict it (Lewis 2003). There are two broad classes of models for retention probability (Dwyer 1997; Jain and Singh 2002)—those that consider a customer defection as permanent ("lost for good") and those that consider a customer switching to a competitor as transient ("always a share").

In the lost-for-good scenario, customer's retention probability has been modeled using hazard rate (Reinartz and Kumar 2000) or similar approaches. Berger and Nasr (1998) discussed various lost-for-good models and illustrate them with numerical examples. Blattberg, Getz, and Thomas (2001) also used a lost-for-good modeling approach and showed how it can be used in conjunction with a customer database. Gupta and Lehmann (2003) argued that under a variety of conditions it may be appropriate to consider a constant margin ($m = p - c$) and constant retention rate (r) per time period so that retention probability in period t is simply r^t. Using infinite time horizon, CLV greatly simplifies to the following expression:

$$CLV = \sum_{t=0}^{\infty} \frac{(p-c)r^t}{(1+i)^t} = m \frac{r}{(1+i-r)} \qquad (2)$$

In other words, CLV simply becomes margin (m) times a *margin multiple* [$r / (1 + i - r)$]. When retention rate is 90% and discount rate is 12%, the margin multiple is about four. Gupta and Lehmann (2005) show how Equation 2 can be modified when margin and retention rates are not constant.

In the second class of models, customers are allowed to switch among competitors, and this is generally modeled using a Markov transition probability matrix. Pfeifer and Carraway (2000) defined the transition states based on customers' recency of purchases as well as an additional state for new or former customers. In this case, CLV is

$$\mathbf{V}^T = \sum_{t=0}^{T} [(1+i)^{-1}\mathbf{P}]^t \mathbf{R} \qquad (3)$$

where $\boldsymbol{V}^T$ is the vector of expected present value or CLV over the various transition states, $\boldsymbol{P}$ is the transition probability matrix, which is assumed to be constant over time, and $\boldsymbol{R}$ is the reward or margin vector, which is also assumed to be constant over time. Rust, Lemon, and Zeithaml (2004) used a similar approach, but they defined $\boldsymbol{P}$ as brand-switching probabilities that vary over time as per a logit model, and they broke $\boldsymbol{R}$ into two components—customer's expected purchase volume of a brand and customer's probability of buying a brand at time t.

Which of the two approaches is better? Rust, Lemon, and Zeithaml (2004) argued that the lost-for-good approach understates CLV, since it does not allow a defected customer to return. Others have argued that this is not a serious problem since the reacquired customers can be treated as new customers. It is possible that the choice of modeling approach depends on the context. For example, in many industries (e.g., cellular phone, cable TV, or banking), customers are usually monogamous, maintaining a relationship with only one company. In other contexts (e.g., consumer goods, airlines, or business-to-business relationships), consumers simultaneously conduct business with multiple companies, and the always-a-share approach may be more suitable.

What time period (T) should be used for estimating CLV? Most researchers have either used a finite time horizon (usually two to three years) based on data availability or an infinite time horizon, since it simplifies the mathematics. Many practitioners argue that it is futile to estimate CLV beyond a two-to-three-year time horizon due to significant errors in forecasting. Recently Malthouse and Blattberg (2003) used data from 135 companies to assess the predictive accuracy of CLV. They used a two-year period to estimate and predict CLV based on RFM (recency, frequency, and monetary-value) measures. This prediction was compared with customer value based on the future one to five years of actual purchase behavior. They found that the predictive accuracy (R^2) of customer value deteriorates only slightly in going from one to five years.

Several studies have provided a conceptual link between customers and shareholder value (Srivastava, Shervani, and Fahey 1998; Hogan et al. 2002; Mulhern 1999). A few recent papers have empirically established this link. These papers suggest that the sum of CLV across all current and future customers (which has also been called *customer equity,* or CE) should provide a strong proxy for firm value. Gupta, Lehmann, and Stuart (2004) formalized this idea and showed that

$$CE = \int_{k=0}^{\infty} \int_{t=k}^{\infty} n_k m_{t-k} e^{-ik} e^{-\left(\frac{1+i-r}{r}\right)(t-k)} dt\, dk - \int_{k=0}^{\infty} n_k c_k e^{-ik} dk \quad (4)$$

where n_k is the number of newly acquired customers for cohort k, m is the margin, r is the retention rate, i is the discount rate, and c is the acquisition cost per customer. Each component in equation (4) can be further modeled. For example, Gupta, Lehmann, and Stuart (2004) estimated the number of new customers acquired in the future using a diffusion-type model. Rust, Lemon, and Zeithaml (2004) used a simpler approach, estimating CLV for an average American Airlines customer and multiplying it by the number of U.S. airline passengers to arrive at its CE.

What We Know. One of the uses of estimating CLV is to rank-order customers or to classify them into tiers based on their expected profitability. This then allows firms to allocate appropriate resources to high-value versus low-value customers. However, this allocation may be misdirected if CLV classification is inaccurate. Results in this area have been somewhat conflicting. Reinartz and Kumar (2003) found that for 90% of customers their model correctly predicted no purchases in the next three-year period. Using a large dataset of a Dutch insurance company, Donkers, Verhoef, and de Jong (2003) found that simple models (e.g., assuming constant margin over time) outperform complex models (e.g., multivariate probit) in predicting CLV at an individual level. Further, about 80% of customers were correctly classified in one of the four quartiles, and the mean absolute deviation was about 17% of the median CLV. In contrast, Malthouse and Blattberg (2003) classified customers into two tiers based on the 80-20 rule. They found that while only 15% of the bottom 80% customers were misclassified, almost 55% of the actual best customers (top 20%) were misclassified. This misclassification was even more severe (81%) for the top-5% customers.

An alternative approach to classify customers is to score them based on their RFM measures. Many models for RFM scoring have been developed over the years (e.g., Hughes 2000; Colombo and Jiang 1999). Using a CLV model, Reinartz and Kumar (2003) selected the top 30%, 50%, and 70% of customers and found their profitability over the next 18 or 30 months to be 25% to 127% higher than the comparable customer groups selected based on RFM scores.

RFM and CLV do not have to be competing models. A key input in predicting CLV is a customer's past purchase behavior, which is captured by RFM measures. Therefore, several researchers have modeled CLV as a function of RFM measures. Malthouse and Blattberg (2003) used a linear regression with CLV of future periods as dependent variables and RFM as independent variables. They found monetary value to be the most important predictor of CLV, followed by frequency and recency. They also found monetary value and frequency to be highly correlated and independent of recency. In contrast, Fader, Hardie, and Lee (2004), using CDNOW data, found recency and frequency to be highly correlated. They linked RFM and CLV using a two-component stochastic model—the first component used an NBD/Pareto model to capture expected number of purchases over a time period, and the second component used a gamma-gamma model to capture monetary value.

Several studies have explicitly built the link between acquisition, retention, and CLV. Reichheld (1996) suggested that the longer a customer stays with a firm, the more profitable they become. While Reinartz and Kumar (2000) found results that contradict Reichheld, Lewis (2004a) found supporting evidence. Recently, Reinartz, Thomas, and Kumar (2004) proposed a three-equation model that linked acquisition (a probit model), duration, and customer profitability (conditional regression models). This allowed them to find optimal budgets for acquisition and retention. They found that even large deviations (e.g., 10%) in either acquisition or retention expenditures from their optimal levels had minimal impact (less than 1%) on CLV. Further, underspending, especially on retention, had a greater detrimental effect on CLV than overspending.

Researchers have also examined the impact of marketing mix variables on CLV. Many earlier studies focused on maximizing a firm's short-term profitability in the context of direct-mailing decisions for catalog industries. These studies built models of response and compared the benefit from this expected response to the cost of mailing (e.g., Bult and Wansbeek 1995). Later, consistent with the concept of CLV, researchers emphasized profit maximization over a long planning horizon (e.g., Bitran and Mondschein 1996). Gonul and Shi (1998) went one step further by formulating a model in which both the firm and the customers are strategic and forward-looking.

Lewis (2004a) proposed a model in which customers' past purchase behavior as well as marketing variables such as price affect customers' decision to buy or renew a newspaper subscription. The forward-looking behavior of customers was captured through a dynamic programming approach. Policy experiments showed that changes in price had a dramatic impact on CLV. In the context of a cellular-phone company, Iyengar (2004) built a structural model to capture the impact of nonlinear prices of a wireless plan on consumers' choice of phone plan, consumption of minutes each month, and decision to stay or defect from the firm. Through policy experiments, he found that changes in fixed or access price (e.g., $30 for 300 free minutes) for the cellular-phone service had a greater impact on CLV than corresponding changes in marginal prices (e.g., $0.40 for every minute over plan usage). Specifically, he found that a 5% decrease in access price could increase the CLV for light users by as much as 10%.

Villanueva, Yoo, and Hanssens (2003) used a vector autoregressive model for an Internet firm to show how the choice of various communication vehicles such as direct marketing, advertising, public relations, and word of mouth generate customers with different CLV. Venkatesan and Kumar (2004) estimated CLV using two separate models of customers' purchase frequency and contribution margin. Both of these components in turn depend on rich (e.g., face-to-face) and standard (e.g., direct mail, telephone) channels of communication. This modeling approach enabled both Villanueva, Yoo, and Hanssens (2003) and Venkatesan and Kumar (2004) to optimally allocate a firm's budget across various communication modes.

Rust, Lemon, and Zeithaml (2004) constructed a CLV and CE model that depends on various marketing programs such as quality, price, convenience, and ad awareness. They found that if American Airlines could increase its quality by .2 of a ratings point on a five-point scale, it would increase its customer equity by 1.39%. Similarly, a $45 million expenditure by Puffs facial tissues to increase its ad awareness by .3 of a ratings point would result in an improvement of $58.1 million in CE.

Few recent studies have empirically demonstrated the link between CE and firm value. Rust, Lemon, and Zeithaml (2004) estimated CE for American Airlines as $7.3 billion, which compared favorably with its

1999 market capitalization of $9.7 billion. Using data for five companies, Gupta, Lehmann, and Stuart (2004) showed that CE approximated firm market value quite well for three of the five companies (exceptions were Amazon and eBay). In addition, they assessed the relative importance of marketing and financial instruments by showing that a 1% change in retention affected CE by almost 5%, compared to an impact of only .9% due to a similar change in discount rate.

What We Don't Know. Most of the research on CLV has implicitly assumed that the value of a customer is independent of other customers. This may not be true if we consider customer portfolio and network effects. Dhar and Glazer (2003) argued that traditional models of CLV ignore uncertainty in customers' profitability: Two customers with the same mean but different variances in CLV are not equally valuable to a firm. They suggest that a firm should not consider a customer in isolation but instead form an optimal customer portfolio based on risk and return, just like a stock portfolio.

In many situations, customer network effects can be strong, and ignoring them may lead to underestimating CLV. Hogan, Lemon, and Libai (2003) showed that word of mouth or direct network effects can be quite substantial for online banking. Often there are also strong indirect network effects (Gupta 2004): For example, firms such as eBay and Monster.com have two related populations (buyers and sellers, or job seekers and employers), and growth in any one population affects the growth of the other populations. Gupta, Lehmann, and Stuart (2004) speculated that omission of these effects may be one of the reasons their CE estimate fell substantially below eBay's market value.

In many industries (e.g., credit cards, insurance, wireless phones, catalogs), customer-based metrics such as CLV appear to be appropriate. However, it is unclear whether these metrics are equally suitable for other industries such as consumer packaged goods, automobiles, pharmaceuticals, or oil drilling. What characteristics of an industry make CLV appropriate? Is CLV relevant only in the relationship context? The only study that has recently addressed this issue is by Yoo and Hanssens (2004), who showed that CLV can be a useful metric in the product-marketing context as well.

Finance theory has long suggested the option value of securities. More recently, this literature has argued for valuing assets as real options. In other words, for most investments, a manager has an option, but not an obligation, to make certain decisions. This flexibility leads to additional value. Put differently, net present value generally undervalues an asset compared to the real option analysis (Copeland 2003). To the extent that customers are also assets and managers have the option to invest in them, they can also be considered as real options. If this is indeed true, then the current models of CLV and CE, which are based on NPV formulation, may be systematically undervaluing customers.

Customer acquisition

Definition and Overview. Customer acquisition refers to the first-time purchase by new or lapsed customers. Research in this area focuses on the factors that influence the buying decisions of these new customers. It also attempts to link acquisition with customers' retention behavior, as well as CLV and CE.

Modeling. The basic model for customer acquisition is a logit or a probit. Specifically, customer j buys as follows (i.e., $Z_{jt} = 1$):

$$\begin{aligned} Z^*_j &= \alpha_j X_j + \varepsilon_j \\ Z_j &= 1 \quad \text{if } Z^*_j > 0 \\ Z_j &= 0 \quad \text{if } Z^*_j \le 0 \end{aligned} \tag{5}$$

where X_j are the covariates and α_j are consumer-specific response parameters. Depending on the assumption of the error term, one can obtain a logit or a probit model (Thomas 2001; Lewis 2004b).

While intuition and some case studies have suggested that acquisition and retention should be linked (Reichheld 1996), early work in this area assumed these two outcomes to be independent (Blattberg and Deighton 1996). Later, Hansotia and Wang (1997) indirectly linked acquisition and retention by using a logit model for acquisition and a right-censored Tobit model for CLV. More recently, several authors have explicitly linked acquisition and retention. A retention equation models the duration of relationship of acquired customer j (y_j) as

$$y_j = \beta_j W_j + \mu_j \qquad (6)$$

Equation 6 either uses y_j and models it as a Tobit (Thomas 2001) or uses $\ln(y_j)$ and models it as a conditional regression (Thomas, Blattberg, and Fox 2004). If a customer's relationship duration is longer than the observation period, then the likelihood function accounts for this right censoring. Equations 5 and 6 are linked by specifying a joint distribution of the errors in the two equations. Response parameters (α_j and β_j) can be estimated at a segment level using latent class analysis or at an individual level using Bayesian methods. Reinartz, Thomas, and Kumar (2004) further linked retention duration to CLV using a regression equation.

The purchase probability of a customer multiplied by the number of customers targeted by a company can provide a straightforward estimate of the expected number of new customers in the next period. However, this ignores the word-of-mouth, or diffusion, effect. Some researchers (e.g., Kim, Mahajan, and Srivastava 1995) have followed the diffusion modeling tradition to forecast the number of new customers. For example, Gupta, Lehmann, and Stuart (2004) suggested the following model for forecasting the number of new customers at time t:

$$n_t = \frac{\alpha\gamma\exp(-\beta-\gamma t)}{[1+\exp(-\beta-\gamma t)]^2} \qquad (7)$$

where α, β, and γ are the parameters of the customer growth curve. It is also possible to include the marketing mix covariates in this model as suggested in the diffusion literature.

What We Know. Using data for airline pilots' membership, Thomas (2001) showed the importance of linking acquisition and retention decisions. She found that ignoring this link can lead to CLV estimates that are 6% to 52% different from her model. Thomas, Blattberg, and Fox (2004) found that while low price increased the probability of acquisition, it reduced relationship duration. Therefore, customers who may be inclined to restart a relationship may not be the best customers in terms of retention.

Lewis (2003) showed that promotions that enhance customer acquisition may be detrimental in the long run. He found that if new customers for a newspaper subscription were offered regular price, their renewal probability was 70%. However, this dropped to 35% for customers who were acquired through a $1 weekly discount. Similar effects were found in the context of Web-based grocery stores, where renewal probabilities declined from 40% for regular-priced acquisitions to 25% for customers acquired through a $10 discount. On average, a 35% acquisition discount resulted in customers with about half the CLV of regularly acquired customers. In other words, unless these acquisition discounts double the baseline acquisition rate of customers, they are detrimental to the CE of a firm. These results are consistent with the long-term promotion effects found in scanner data for consumer packed goods (Jedidi, Mela, and Gupta 1999).

In contrast, Anderson and Simester (2004) conducted three field studies and found that deep price discounts have a positive impact on the long-run profitability of first-time buyers but a negative longterm impact on established customers. The dynamics of pricing was also examined by Lewis (2004a) using a dynamic programming approach. He found that for new customers, price sensitivity increases with time lapsed, while for current customers it decreases with time as a buyer. Therefore, optimal pricing involves offering a series of diminishing discounts (e.g., $1.70 per week for new newspaper subscribers, $2.20 at first renewal, $2.60 at second renewal, and full price of $2.80 later) rather than a single deep discount.

What We Don't Know. Most direct-marketing programs have a very low response rate. While a 1%–2% response rate is typical, response rates of .1% are not unusual. This poses some challenges in modeling rare events. One possible approach is to oversample rare events and later correct for this oversampling. While these methods exist for homogeneous populations (King and Zeng 2001), approaches that include customer heterogeneity are needed.

Practitioners rely on experimentation rather than statistical modeling to solve this problem. They argue that most applications involve millions of customers and that it is relatively easy to conduct experiments that can reveal significant differences across treatments, even if response rate among consumers is very low. It is interesting that while academics have traditionally focused on building sophisticated models (and devising complex sampling techniques to deal with the rare-events issue), industry has approached this problem in a simpler way, through experiments. Recent work by Anderson and Simester (2004) has also used field experiments. It will be useful to compare the advantages and disadvantages of these two approaches.

Acquisition costs are critical for acquisition budget allocation and for evaluating a firm's CE. Most studies either ignore these costs or assume them to be constant. Although some researchers have argued that acquisition costs may increase exponentially as more and more customers are acquired (Blattberg and Deighton 1996), no studies empirically validate these claims. The absence of research in this area stems partly from the difficulty of obtaining cost information as well as the difficulty in allocating many elements of marketing costs (e.g., advertising) at an individual-customer level. Niraj, Gupta, and Narasimhan (2001) is one of the few studies that explicitly allocates costs to individual business customers.

Customer retention

Definition and Overview. Customer retention is the probability of a customer being "alive" or repeat buying from a firm. In contractual settings (e.g., cellular phones, magazine subscriptions), firms clearly know when a customer terminates the relationship. However, in noncontractual settings (e.g., buying books from Amazon), a firm has to infer whether a customer is still active. For example, as of July 2004, eBay reported 114 million registered customers but only 48 million active customers. Most companies define a customer as active based on simple rules of thumb. For example, eBay defines a customer as active if they have bid, bought, or listed on eBay during the past 12 months. In contrast, academic researchers rely on statistical models to assess the probability of retention.

Modeling. As indicated earlier, there are two broad classes of retention models. The first class considers customer defection permanent and typically uses hazard models to predict probability of customer defection. The second class considers customer switching to competitors as transient and typically uses migration or Markov models. We briefly discuss each class of models.

Previously, we discussed how retention or repeat purchase is modeled as conditional regression along with customer acquisition (see Equation 6). This regression equation uses purchase duration y or $\ln(y)$ as the dependent variable as a function of covariates. Retention is linked to acquisition through the error correlation between the two models (Thomas 2001; Thomas, Blattberg, and Fox 2004; Reinartz, Thomas, and Kumar 2004).

An alternative approach is to explicitly use hazard or survival models. These models fall into two broad groups—accelerated failure time (AFT) or proportional hazard (PH) models. The AFT models have the following form (Kalbfleisch and Prentice 1980):

$$\ln(y_j) = \beta_j W_j + \sigma\mu_j \quad (8)$$

Notice the similarity between equations 6 and 8. If σ = 1 and μ is normally distributed, we get the model used in Equation 6. If σ = 1 and μ has an extreme value distribution, we get an exponential duration model with constant hazard rate. Different specifications of σ and μ lead to different models such as Weibull or generalized gamma. Allenby, Leone, and Jen (1999), Lewis (2003), and Venkatesan and Kumar (2004) used a generalized gamma for modeling relationship duration.

Proportional hazard models are another group of commonly used duration models. These models specify the hazard rate (λ) as a function of baseline hazard rate (λ_0) and covariates (*W*):

$$\lambda(t;W) = \lambda_0(t)\exp(\beta W) \quad (9)$$

Different specifications for the baseline hazard rate provide different duration models such as exponential, Weibull, or Gompertz. This approach was used by Bolton (1998) and Gonul, Kim, and Shi (2000).

Schmittlein, Morrison, and Colombo (1987) and Schmittlein and Peterson (1994) proposed a NBD/Pareto model for assessing the probability that a customer is still alive. This model makes five assumptions: (a) while alive, customer purchases are distributed Poisson with a rate λ; (b) each customer remains alive for a lifetime, which has an exponential distribution with a death rate μ; (c) consumer heterogeneity in purchase rate is distributed gamma; (d) consumer heterogeneity in death rate is distributed according to another gamma distribution; and (e) purchase and death rates are independent. This results in an NBD/Pareto model that is estimated using the recency and frequency of a customer's past purchases. Reinartz and Kumar (2000) used this model to estimate *P*(alive). They further used an arbitrary cutoff such that if *P*(alive) > .5, a customer is deemed to be alive. Some authors have questioned the assumptions of NBD/Pareto model. For example, Malthouse and Blattberg (2003) argued that it is highly unlikely that consumer purchases in a catalog industry follow a Poisson process.

Instead of modeling duration of relationship, one can model whether or not a customer is likely to defect in a prespecified time period (e.g., the probability of a wireless customer defecting in the next month). This is a form of discrete-time hazard model. Using data from a "churn tournament" in which 33 academic and industry participants submitted 44 entries, Neslin et al. (2004) found that logit and tree models outperformed (in terms of prediction as measured by top-decile lift and Gini coefficient) other approaches such as discriminant analysis. The winning entry in this tournament was based on a tree approach, in which decision trees were fitted on the residuals of the previous decision trees. Each tree was relatively small, with about nine nodes, but the method used a large number (as many as 3,000) of such trees. Predictions were based on a weighted average of these trees. Lemmens and Croux (2003) showed that techniques such as bagging and boosting can further enhance the predictive power of these classification trees.

A customer-migration approach typically uses Markov models to estimate transition probabilities of a customer being in a certain state. Bitran and Mondschein (1996) defined these states based on RFM measures. Rust, Lemon, and Zeithaml (2004) used brands as states and estimated transition probabilities using a logit model. Iyengar (2004) defined wireless phone plans as well as customer defection as states and used a structural model to obtain transition probabilities. Simester, Sun, and Tsitsiklis (2004) used a binary tree approach to define the state space and estimated the transition probabilities using a nonparametric approach.

What We Know. Reichheld (1996) emphasized the importance of customer retention for firm profitability. Reichheld and Sasser (1990) found that a 5% increase in customer retention could increase firm profitability from 25% to 85%. However, Reinartz and Kumar (2000) argued against this result, suggesting "it is the revenue that drives the lifetime value of a customer and not the duration of a customer's tenure" (p. 32). Reinartz and Kumar (2002) further contradicted Reichheld based on their research findings of weak to moderate correlation (.2 to .45) between customer tenure and profitability across four datasets. However, their conclusions are surprising because, by definition, CLV depends both on revenues and on retention probability or customer tenure. Further, a correlation of .2–.45 is quite substantial. Recent studies (e.g., Lewis 2004a) have supported rather than contradicted Reichheld's conclusions. Gupta, Lehmann, and Stuart (2004) also found that retention rates have a significant impact on firm value.

What drives customer retention? In the context of cellular phones, Bolton (1998) found that customer satisfaction with the firm had a significant and positive impact on duration of relationship. As customers gained more experience with the firm, this prior satisfaction gained even more importance. She also found that while access time had no impact on duration, airtime price had a negative impact. Iyengar (2004) also examined customer defection for a cellular-phone provider and found that underage and overage (i.e., number of minutes used below or over the plans) significantly affected defection.

Lewis (2004b) found that depth of acquisition discount was negatively related to retention duration for newspaper subscribers. In their study of the luxury-car market, Yoo and Hanssens (2004) found that discounting increased acquisition rate for Japanese cars, but it increased retention rate for American brands. They also found product quality and customer satisfaction to be highly related to acquisition and retention effectiveness of various brands. Based on these results, they concluded that if customers are satisfied with a high-quality product, their repeat purchase is less likely to be affected by that brand's discounting. They also found that advertising did not have any direct significant impact on retention rates in the short term.

Venkatesan and Kumar (2004) found that frequency of customer contacts had a positive but nonlinear impact on customers' purchase frequency. Reinartz, Thomas, and Kumar (2004) found that face-to-face interactions had a greater impact on duration, followed by telephone and email interactions. Reinartz and Kumar (2003) found that duration was positively affected by customers' spending level, cross-buying, number of contacts by the firm, and ownership of firm's loyalty instrument.

What We Don't Know. Since the introduction of the frequent-flier program by American Airlines in the 1980s, loyalty programs (LPs) have become ubiquitous in almost every industry. Interest in LPs has increased over time as more and more companies have used them for developing relationships, stimulating product or service usage, and retaining customers. In spite of the pervasiveness of LPs, their effectiveness is far from clear. Some studies have found that they increase customer retention (Bolton, Kannan, and Bramlett 2000); others have found no impact on retention but improvement in share of wallet (Sharp and Sharp 1997); and yet others have found almost no difference in the behavior of LP members and nonmembers (Dowling and Uncles 1997). Even if LPs work, which customers do they work for the best? Conventional wisdom suggests that LPs should be designed to reward a firm's best customers. However, a recent study by Lal and Bell (2003) found that in the context of grocery stores, LPs had the biggest impact on a store's worst (or lowest-spending) customers.

The success of LPs is contingent on their structure and design. However, it is unclear how they should be designed. Should cash or merchandise be the promotional reward? Should luxury or necessity rewards be used? Should the reward be probabilistic or guaranteed? Is it better to offer the firm's own product as a reward or cater to consumers' desire for variety and offer different (e.g., partner) rewards? Recent research in consumer behavior provides some guidelines (e.g., Kivetz and Simonson 2002). However, most of this work has been done primarily in experimental/lab settings, and it will be useful to test some of these propositions in field settings.

One of the challenges in studying the effectiveness of LPs is the issue of endogeneity—customers who sign up for LPs are likely to be different (e.g., heavier buyers) than those who don't sign up for these programs. Therefore a simple comparison of buying behavior of LP members and nonmembers may overestimate the effectiveness of these programs. Leenheer et al. (2003) examined seven supermarkets' LPs and accounted this endogeneity issue through instrumental variables. They found that LPs generally increased share of wallet. However, four out of the seven programs were ineffective.

Most marketing studies either assume or ignore retention costs. Perhaps the current accounting systems of firms make it difficult to separate retention costs from other marketing expenses. As with acquisition costs, some authors have suggested that retention costs may be higher at higher retention rates (Blattberg and Deighton 1996). Although this relationship is critical to determine the optimal retention rate and budget, no empirical study has examined it.

Finally, much work remains to be done in modeling customer defection. The empirical literature in marketing has traditionally favored structured parametric models (such as logistic or probit regression or parametric hazard specifications) that are easy to interpret. In contrast, the vast literature in data mining, machine learning, and nonparametric statistics has generated a plethora of approaches that emphasize predictive ability. These include projection-pursuit models, neural-network models, tree-structured models, spline-based models such as generalized additive models (GAM) and multivariate adaptive regression splines (MARS), and, more recently, approaches such as support vector machines and boosting. These machine-learning approaches remain alien to the marketing literature, not surprisingly because of the tremendous emphasis that marketing academics place on substantive insights and interpretability. Predictions can also be improved by combining models. The machine-learning literature on bagging, the econometric literature on the combination of forecasts, and the statistical literature on model averaging suggest that weighting the predictions from many different models can yield improvements in predictive ability. Clearly, further work is needed to understand the relative merits and disadvantages of these different approaches.

Cross-selling

Definition and Overview. As cost of customer acquisition increases, firms are trying to get the maximum out of their existing customers. One such effort involves cross-selling, or attempting to sell related products to current customers. This involves assessing which products to cross-sell, to whom, and at what time. It also involves the choice of appropriate marketing instruments (e.g., contact strategy or pricing).

Modeling. In many product categories, customers acquire products in some natural sequence. For example, in financial services, customers may start with a checking or savings account and over time buy more complex products such as loans and stocks. Kamakura, Ramaswami, and Srivastava (1991) used this observation to argue that a customer is likely to buy a product upon reaching a "financial maturity" that is commensurate with the complexity of the product. This was modeled by positioning both products and consumers along a common latent difficulty/ability dimension. Specifically, the probability that consumer j would buy product k is given by

$$P_{jk} = [1 + \exp\{\alpha_k(\beta_k - O_j)\}]^{-1} \quad (10)$$

where O_j is the position of consumer j and β_k is the position of product k along the latent dimension.

Recently, Li, Sun, and Wilcox (2004) used a similar conceptualization for cross-selling sequentially ordered financial products. Instead of using a logistic model, they used a multivariate probit model. This model was earlier posited by Manchanda, Ansari, and Gupta (1999) to model consumer purchases of multiple product categories. Here,

$$\begin{aligned} \mathbf{u}_{jt} &= \mathbf{X}_{jt}\beta_j + \varepsilon_{jt} \\ \varepsilon_{jt} &\sim MVN(\mathbf{0}, \Sigma) \end{aligned} \quad (11)$$

where $\boldsymbol{u}_{jt}$ is the vector of utilities for consumer j at time t for multiple products, $\boldsymbol{X}$ are covariates, and $\boldsymbol{\varepsilon}$ are the errors that are correlated across products. Li, Sun, and Wilcox (2004) used latent dimension of Kamakura, Ramaswami, and Srivastava (1991) and ownership of previous products as two of the covariates in Equation 11. Verhoef, Franses, and Hoekstra (2001) used an ordered probit model to model consumers' cross-buying. Knott, Hayes, and Neslin (2002) used logit, discriminant analysis, and neural network models to predict the next product to be bought.

The models discussed so far focus only on which product a customer is most likely to buy next. Knott, Hayes, and Neslin (2002) augmented their choice model with a hazard model to predict the timing of this purchase. Kumar, Venkatesan, and Reinartz (2004) also modeled both purchase timing and what product a customer is likely to buy. They used a multinomial probit model for choice and a log-logistic hazard model for interpurchase time. In principle, these models are similar to the choice and incidence models used by researchers many years ago to model consumer purchases in scanner panel data (e.g., Gupta 1988). Many researchers have simply augmented these models by including current ownership of product A as a covariate to predict purchase behavior of product B.

Kamakura, Kossar, and Wedel (2004) used a multivariate split hazard model to find physicians' propensity to *ever* prescribe a drug as well as the timing of their adoption. The likelihood for physician j to prescribe drug k is

$$L_j = \prod_{k \in C_j} \theta_{jk} f(t_{jk}) \prod_{k \notin C_j} [\theta_{jk} S(t_{jk}) + (1 - \theta_{jk})] \quad (12)$$

where θ_{jk} is the probability that physician j will ever prescribe drug k (this allows for the possibility that some physicians would never adopt a drug, hence the name split hazard), C_j is the set of drugs adopted by physician j, f is the density function, and S is the survival function for adoption time.

What We Know. Do the cross-selling models predict well? In general, the answer is yes. Knott, Hayes, and Neslin (2002) found that the predictive accuracy of their model was 40% to 45%, compared to a random guess of about 11% to 15%. Interestingly, different methods (e.g., logistic regression, discriminant analysis, and neural networks) performed roughly the same. In addition, they found that their model had an ROI of 530%. In contrast, the bank in Knott, Hayes and Neslin's study used a heuristic for mailing loan applications to households with home value of more than $100,000. This method produced a negative ROI. Another way to show predictive performance of a model is through a gains chart. This chart shows that if customers are picked randomly, then the top, say, 30% customers should account for

30% of the purchases. Li, Sun, and Wilcox (2004) found that, using their model, the top 30% customers accounted for 70% of the cross-category purchases.

Many studies have focused only on what product a customer is likely to buy next, while others have also attempted to predict when this purchase is likely to happen. Does it improve profitability if we predict the timing of purchase in addition to what product a customer is likely to buy next? Knott, Hayes, and Neslin (2002) showed that including a hazard incidence model to their next-product-to-buy model improves profits by about 25%.

What factors influence consumers' decision of what to buy next? In the context of banking products, Kamakura, Ramaswami, and Srivastava (1991) and Li, Sun, and Wilcox (2004) have suggested that it is the distance between a consumer's financial maturity and a product's complexity. For high-tech products, Kumar, Venkatesan, and Reinartz (2004) found that proportion of same-category purchases and depth of purchases with high processing capacity (e.g., faster computers) had a positive influence on cross-selling.

While many researchers found that ownership of one product is a powerful predictor of the next product purchase, others have found weak evidence for this. In contrast to Bolton (1998) and Bolton and Lemon (1999), Verhoef, Franses, and Hoekstra (2001) found that satisfaction and payment equity (or perceived fairness of price) with an existing product of an insurance company had no impact on cross-buying of another product. In contrast to Ainslie and Rossi (1998), Iyengar, Ansari, and Gupta (2003) questioned the value of using a consumer's price sensitivity in one category to predict their price sensitivity in another category.

What We Don't Know. Most of the research in this area has explored products (e.g., banking or hardware-software) that have a natural sequence of product ownership, which makes the task of predicting the next product to buy relatively easier. However, many companies face a much tougher situation where such natural sequencing does not exist. It will be useful to see if cross-selling models can improve predictions over simple conditional tables.

Many firms believe that cross-selling improves customer retention. In other words, customers who buy multiple products from a firm are likely to be more loyal. This may indeed be true. However, the evidence to date is generally correlational. It is quite possible that the causality goes in the opposite direction, i.e., customers who are more loyal to a firm tend to buy multiple products. If cross-selling does indeed enhance customer loyalty, then it also has strong implications for pricing of subsequent products sold to a customer. Almost no research has been done in this area.

Future Challenges

In the previous sections, we discussed future research issues for each construct or measure. Stepping back from individual constructs, we see several major research challenges that must be addressed to move customer metrics forward.

As we are developing metrics that capture customer behavior, do we continue to need the perceptual constructs?

In spite of the popularity of perceptual measures (e.g., customer satisfaction) among both academics and practitioners, it is surprising to find that very few studies have directly incorporated them in behavioral outcome (e.g., CLV) models. There are at least three reasons for this lack of connection. First, in academia there are two parallel groups of researchers, those who primarily work with perceptual measures and those who focus mainly on behavioral outcomes, with very little interaction between the two groups. This is often also true in companies, where two different groups of researchers handle customer data—a marketing research group deals with complex modeling techniques, and a customer satisfaction group deals with survey feedback. Second, perceptual data are usually collected for a sample of customers through surveys, whereas behavioral data are available for the entire customer base based on transaction data. Therefore, merging the two datasets also requires handling of "missing" observations for a large number of customers. Third, survey data are usually collected anonymously, making researchers' ability to connect it with customers' behavioral data difficult if not impossible. In fact, when companies use outside research vendors to collect perceptual data, they often must sign agreements that preserve respondent anonymity.

If the behavioral outcome models have been useful in predicting customer behavior and linking marketing actions to firm value, do we really need *any* intermediate perceptual measures? A few papers that have attempted to include these perceptual measures into outcome models (e.g., Bolton 1998; Verhoef, Franses, and Hoekstra 2001) have found conflicting evidence about the value of these constructs. However, the findings are currently insufficient to judge the value of perceptual constructs.

If perceptual feedback could be linked to behavioral outcomes, and on a more widespread basis, we would understand whether the perceptual measures do predict behavioral outcomes. If they do, they remain critical for all of the reasons suggested earlier. If they do not, their benefit is more limited to diagnosis of drivers of overall perceptual outcomes (i.e., the drivers of service quality, which could be then used to address service problems), tracking customer perceptions, and comparing them with perceptions of competitors' customers.

Do we need all of the perceptual constructs?

This survey of customer metrics has made one thing very clear: Considerable overlap exists in definition and measurement of the constructs on which customer metrics are based. For this reason, strong correlations are present among the constructs. Research studies have focused on different pairs or combinations of variables, and the pattern of relationships among the variables is not clear.

For example, more than 30 empirical studies measure both service quality and customer satisfaction, many of them in an effort to differentiate the constructs from each other and to determine the directionality of the relationship between them. Significantly, practitioners typically use the terms interchangeably and measure them in similar ways. While some academic researchers have acknowledged the interchangeability of the constructs (Rust, Zahorik, and Keiningham 1995), most have attempted to be very precise about the differences between service quality and customer satisfaction, resulting in considerable debate (Parasuraman, Zeithaml, and Berry 1994; Oliver 1997; Bitner and Hubbert 1993; Iacobucci, Grayson, and Ostrom 1994; Cronin, Brady, and Hult 2000). There remains a lack of consensus in the literature about these issues, perhaps due to the lack of resolution about whether customer satisfaction is a transaction-specific or global assessment. One integrative framework that reflects and reconciles these differing perspectives (Parasuraman, Zeithaml, and Berry 1994) states that global impressions about a firm stem from an aggregation of transaction experiences. In each transaction-specific evaluation, perceptions of service quality, product quality, and price combine to provide a transaction-based assessment of satisfaction. The aggregation of these transaction-specific assessments can lead to global assessments of satisfaction, service quality, product quality, and price. This framework, in addition to capturing the notion that the service-quality and customer-satisfaction constructs can be examined at both transaction-specific and global levels, is consistent with the multidirectional findings of previous research.

While other variables have not been studied as comprehensively as customer satisfaction and service quality, we can start to identify patterns that suggest that not all constructs are equally appropriate in all situations. For example, there seems to be an emerging recognition that customer satisfaction is most appropriate for business-to-consumer situations, but trust or commitment are more appropriate for business-to-business situations. Garbarino and Johnson (1999) showed that for low relational customers (transactional customers), satisfaction is the primary mediating construct between attitudes and future intentions. For high relational customers (relationship customers), trust and commitment rather than satisfaction are the mediators. This is consistent with Oliver's (1999) position that customers will not feel loyalty for every type of product, and that for some products (e.g., chewing gum), customer satisfaction is all that a company can aspire to. While banks would like to develop strong relationships with their customers and are moving toward using loyalty measures rather than satisfaction, many customers do not want relationships with their banks. It may be that attempting to measure something stronger than customer satisfaction or service quality is not worthwhile.

Not enough studies have been conducted with combinations of the other variables to understand their interrelationships. Perhaps a more critical question is whether we should spend more time looking at the interrelationships or simplify the study of these perceptual concepts, perhaps by identifying why they are useful to managers and researchers and then evaluating which ones are most desirable. The definitions, measures, and studies discussed in this paper provide a basis for attempting such a simplification and sorting.

Do we have a comprehensive view of customer metrics, and what are the links among various metrics?

Figure 1 presents a simple yet comprehensive view of how marketing actions lead to customer perceptions and behavior, which in turn influence a firm's financial performance. However, most studies have examined only a few of the links in this system. For example, Rust and Zahorik (1993) examined the relationship between customer satisfaction and customer retention in a retail-bank setting and found a positive link. Verhoef, Franses, and Hoekstra (2001) showed a positive effect of commitment on cross-buying of financial services.

Kamakura et al. (2002) is one of the few studies that has taken a comprehensive view, empirically investigating the service profit chain that links operational inputs (e.g., investment in personnel or ATMs in a bank), customers' perceptions, customer behavior, and firm profit. Using a survey of over 5,000 customers from 500 branches of a national Brazilian bank, the authors found that superior satisfaction alone is not an unconditional guarantee of profitability. In fact, their results showed that bank branches that focus on either operational efficiency or customer retention alone are less profitable. They also found a nonlinear relationship between customers' intentions and their actual behavior.

We need more studies that take a comprehensive view of customers rather than examining only a few constructs at a time. These studies can help us understand how various constructs are related, which constructs mediate others, which constructs lag or lead other constructs, and how these relationships change by contexts and industries. This should eventually lead us to empirical generalizations.

How do we account for endogeneity?

Customer metrics help a firm in identifying high-value and low-value customers as well as in designing appropriate customer offers. For example, catalog companies group customers into deciles based on their past purchase behavior. The most responsive or high-value group receives more catalogs than the low-value group. Similarly, in the airline industry, a frequent flier receives better treatment than an infrequent flier. In other words, low-value customers get a lower service level, lower status in loyalty programs, and lower overall benefits.

However, this could be a self-fulfilling prophecy, where low level of investment in a customer leads to lower customer profitability, which in turn leads to an even lower level of investment from the firm. In other words, it is not only the customers who are responding to a firm's actions, but it is also the firm that is responding to customers' behavior. Most customer metrics and models ignore this endogeneity issue, assuming instead that a customer's value over their lifetime is given; our task is to estimate it and use this estimate to provide service that is commensurate with the value of a customer.

How can we account for competition?

It is ironic that even as company databases are growing larger and models and measures are becoming more sophisticated, they ignore competition and thus provide an incomplete and sometimes misleading picture. For example, although one firm's service quality may be improving over time, this improvement may have no impact on customer satisfaction if the service quality of competitors is improving even faster. Similarly, two customers with the same CLV may have different shares of wallet and therefore different future potential. While customer defection clearly depends on competitive offerings, most models of customer defection do not include such information. This is usually blamed on lack of data—either because customers have no experience with competitors and cannot provide information about their experience with competitors or because a firm does not collect competitor information.

A few studies have found innovative ways to get around these problems. For example, Kamakura et al. (2003) supplemented a bank's internal customer database with a survey of a few thousand customers. Since it is impossible to survey millions of bank customers, they used the data from the survey sample to impute the missing information (e.g., wallet share) for the remaining customers in the database. We need more studies that either use such innovative methods to account for competition or show the potential bias from ignoring this information.

How are customer metrics related to brand metrics?

For more than a decade, marketing has focused quite heavily on brand equity. This literature developed its own set of perceptual (e.g., awareness, association, and attachment), behavioral (e.g., price sensitivity), and financial (e.g., brand value) metrics. Many academic studies show that brand equity forms a large part of a firm's value. Companies such as Interbrand routinely estimate the financial value of brands. Even accountants have taken notice of the intangible value of brands, and there is currently a debate about putting these intangible assets on the balance sheet.

At the same time, research on customer metrics has developed its own set of perceptual, behavioral, and financial metrics. Both academics and practitioners have refined and used measures such as customer satisfaction and customer lifetime value. Recent studies have also shown that customer equity serves as a proxy for firm value.

However, it appears that the two streams have grown almost independently. They use their own metrics and rarely acknowledge that one affects the other. For example, it is unclear how brand and customer equity are different. Is one a subset of the other? Does brand equity affect customer equity, or is it the other way around? Is it possible for a firm to have low brand equity but high customer equity, and vice versa? Rust, Lemon, and Zeithaml (2004) have suggested that brand value is one component of customer equity. However, more work is needed to clarify the distinction and relation between these two important areas.

Conclusion

In this paper, we set out to review and integrate existing knowledge on customer metrics. We provided a simple yet comprehensive framework for customer metrics, examined both perceptual and behavioral metrics, discussed what is known from current research, and suggested directions for future work. We also highlighted several broader challenges that we must address to move this important topic forward.

As marketing comes under increasing pressure and firms feel a greater need to justify their investment in customers, customer metrics will become even more critical. It will be imperative for firms to show that their actions affect customer behavior and the firm's financial performance. We hope that our review and research agenda provide useful guidelines to both academics and practitioners in making these metrics an integral part of firms' decision-making process.

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