

Choosing the Right Metrics to Maximize Profitability and Shareholder Value

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Abstract

There is an ever-present need for managers to justify marketing expenditures to the firm. This can only be done when we can establish a direct link between marketing metrics and future customer value and firm performance. In this article, we assess the marketing literature with regard to marketing metrics. Subsequently, we develop a framework that identifies key metrics that firms should focus on that can give a firm a better picture of how they got to where they are now and insights towards how they can continue to grow into the future. We then identify several organizational challenges that need to be addressed in order for firms to build the capabilities of collecting the right data, measuring the right metrics, and linking those metrics to customer value and firm performance. Finally, we offer guidelines for future research with regard to marketing metrics to help firms establish successful marketing strategies, measure marketing effectiveness, and justify marketing expenditures to top management. Published by Elsevier Inc on behalf of New York University.

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Introduction

“You can’t manage what you don’t measure.”

- Old Management Adage

In recent years, there has been a significant increase in the number and type of marketing metrics that managers can use to measure marketing effectiveness and to develop marketing strategies with the goal of increasing firm performance. The purpose of these marketing metrics is twofold. First, marketing metrics serve to increase marketing’s accountability within the firm and to justify spending valuable firm resources on marketing initiatives to top management (Rust et al. 2004b). Second, marketing metrics can help managers and retailers identify the drivers of future customer and firm value and build link-

ages between marketing strategy and financial outcomes. When retailers are able to identify the drivers of customer and store value, managers can then maximize customer and store profits (Kumar et al. 2006a). The increase in the number of available marketing metrics has been the result of several different factors. First, increases in database technology have given firms the ability to collect more information about their own customers and to an extent some information about competitors and their competitor’s customers. Second, the advent of new channels of distribution for products and services, such as the Internet, has significantly increased the availability and complexity of marketing metrics. Finally, the identification of new drivers of customer and firm value, for example word-of-mouth and referral behavior (Hogan et al. 2003; Kumar et al. 2007; Reichheld 2003), has led to an increase in the number of different types of marketing metrics beyond just measurements of customer value and return on investment.

However, with the abundance of marketing metrics to choose from (see Farris et al. (2006) for a detailed list of relevant marketing metrics), the challenge marketing managers and retailers now face is not whether to use marketing metrics, but instead

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how to determine which metrics are the most important metrics to utilize for a given firm. While there is no single or “silver” metric that can summarize marketing performance (Roberts and Ambler 2006), too many metrics can just provide clutter to the marketing metrics dashboard. Thus, the most appropriate metrics are those that are effective at measuring marketing productivity, help managers to develop effective forward-looking marketing strategies, help predict a customer’s future value to the firm, and help predict the firm’s future financial performance.

Thus, to choose the appropriate metrics it is necessary for managers to answer the following five key questions:

1. What metrics are currently in place in different firms?
2. What metrics should be in place in different firms?

3. How can managers link strategic actions to these new metrics?
4. How do these metrics relate to (a) customer value to the firm and (b) firm performance?
5. What are the challenges firms will face when migrating to these new metrics?

We address these five key questions in the following four sections of this paper. We will first review the key marketing metrics that exist in the marketing literature and in marketing practice. Second, we present a framework that will help managers identify key metrics that should be used by different firms. Third, we discuss the steps firms can follow to migrate to these metrics. We also provide examples of situations in marketing research

Table 1
Discussions on multiple metrics.

Author (year)	Title (journal)	Finding/contribution
Gupta and Zeithaml (2006)	Customer Metrics and Their Impact on Financial Performance (Mktg. Sci.)	Discussion of links between potential unobservable and observable metrics that have been shown to impact financial performance. In addition a call for future research that addresses key controversies in metric-related research. <i>Unobservable:</i> Customer Satisfaction, Service Quality, Loyalty, and Intention to Purchase; <i>Observable:</i> Acquisition, Retention, Cross-selling, Customer Lifetime Value, Customer Equity.
Rust et al. (2004a)	Measuring Marketing Productivity: Current Knowledge and Future Directions (JM)	Introduces a broad framework for assessing marketing productivity based on a review of past and current research. Suggests new paths for research to evaluate marketing productivity. Specifically deals with what we know and what we would like to know with respect to the chain of marketing productivity. The chain includes: Tactical Actions, Strategies, Customer Impact, Marketing Assets, Marketing Impact, Market Position, Financial Impact, Financial Position, Impact on Firm Value, and Value of the Firm.
Farris et al. (2006)	Marketing Metrics: 50+ Metrics Every Executive Should Master (Book)	List and description of major metrics used in academics and practice. These metrics are broken down into 9 main categories. <i>These Categories are:</i> (1) Share of Hearts, Minds, and Markets, (2) Margins and Profits, (3) Product and Portfolio Management, (4) Customer Profitability, (5) Sales Force and Channel Management, (6) Pricing Strategy, (7) Promotion, (8) Advertising Media and Web Metrics and (9) Marketing and Finance.
Ambler (2003)	Marketing and the Bottom Line: The Marketing Metrics to Pump Up Cash Flow (Book)	A book that first argues that multiple metrics are necessary – since there are many different approaches to measuring the same performance. The main focus is on the value of brand equity – noting that it is a complex asset.
Kumar (2008a, b)	Managing Customer for Profit (Book)	The author shows how to use Customer Lifetime Value (CLV) to target customers with higher profit potential, manage and reward existing customers based on their profitability, and invest in high-profit customers to prevent attrition and ensure future profitability. The author introduces customer-centric approaches to allocating marketing resources for maximum effectiveness, pitching the <i>right</i> products to the <i>right</i> customers at the <i>right</i> time, determining when a customer is likely to leave, and whether to intervene, managing multichannel shopping, and calculating a customer’s referral value (CRV).

and practice that identify how firms can overcome certain challenges related to migrating to new marketing metrics. Finally, we will provide guidelines for future research in marketing that will continue to extend our knowledge towards selecting the best marketing metrics that marketing managers can directly link to key financial outcomes.

A review of marketing metrics

The use of marketing metrics was the main result of pressures from top management and shareholders to justify marketing spending. However, the consequence of this growing need for quantitative measures of marketing and firm performance has led to a multitude of metrics measuring everything from levels of customer satisfaction to the number of unique clicks to a specific website. The goal of all of these metrics has been to gain some quantifiable measure of any number of business goals, from measuring the effectiveness of marketing campaigns to proxies of firm value. While it is important for marketing managers to know the entire consideration set of available metrics, that is beyond the scope of this paper. For more complete lists of multiple metrics it is worthwhile to refer to books and journal articles that discuss multiple metrics (Ambler 2003; Farris et al. 2006; Gupta and Zeithaml 2006; Kumar 2008a, b; Rust et al. 2004a,b). In addition, see Table 1 for a discussion of each of these books or articles and the key insights each provides. Instead, we present an assessment of a key set of seven categories of metrics found in the marketing literature that are relevant to retailers. In addition, we also discuss two specific types of marketing metrics with regard to the five key questions this paper sets out to answer. These include: (1) backward-looking versus forward-looking metrics and (2) the customer and brand value metrics that link directly to financial performance and firm value. We discuss how each of these types of metrics have impacted marketing research and practice in addition to how each of these types of metrics relates directly to manager's ability to generate effective marketing strategies.

Assessment of the literature

In this section, we review the literature in marketing that develops or discusses key metrics that can be used by retailers. We break these key metrics in the literature into seven distinct

categories and give examples along with some discussion of literature in each of these categories. These seven categories include:

1. Brand value metrics
2. Customer value metrics
3. Word of mouth and referral value metrics
4. Retention and acquisition metrics
5. Cross-buying and up-buying metrics
6. Multi-channel shopping metrics
7. Product return metrics

Each of these seven categories of marketing metrics relevant to retailers serves two main purposes. First, these retailer marketing metrics can be used for strategic and tactical marketing campaigns. As an example, a marketing manager can strategically use each customer's predicted referral value score to determine which customer to target next time period with referral incentives (Kumar et al. 2007). In addition, a marketing manager can strategically use each customer's predicted value (CLV) to determine which customers to select for a given marketing campaign that encourages cross-buying, up-buying, or multi-channel shopping (Kumar and Petersen 2005). Second, these retailer marketing metrics can be used for short-term or long-term goals and predictions. As an example, in the short-term the goal of the firm may be to increase the general awareness of a given brand. Thus, the firm would try to increase the overall percentage of consumers in the marketplace who are aware of the brand in the following time period (e.g., month or quarter). However, a long-term goal resulting from continuous short-term increases in brand awareness may be to increase overall brand equity, a long-term metric.

The questions that still remain – How does a manager link these different types of metrics to strategic goals and how can these strategic goals be linked directly to customer profitability and shareholder value? The following discussion provides a general sense of the literature in marketing that either identifies specific marketing metrics or builds conceptual or empirical linkages between marketing metrics and customer profitability, shareholder value, or both. We also provide a series of tables that summarize this information (see Tables 2A–2G). We begin by discussing the marketing metrics found in each of the seven categories listed previously.

Table 2A
Examples of brand value and brand equity metrics.

Author (year)	Finding/contribution
Keller (1993) Simon and Sullivan (1993)	The author provides a conceptual model of brand equity from the customer's perspective. A brand's value is the capitalized value of the profits that result from associating that brand's name with specific products and services.
Kerin and Sethuraman (1998)	The authors discuss the link between brand value and shareholder value. The authors find this link to be positive, but the functional form of the relationship is concave (decreasing returns) with respect to the firm's Market to Book Ratio.
Madden et al. (2006)	Using the Fama-French method, the authors find empirical evidence that stronger brands deliver stronger shareholder value with less risk to the firm.
Leone et al. (2006)	The authors provide a discussion on the link between Brand Equity and Customer Equity. The authors show that while the literature has been divergent in nature, there are great similarities between the two.

Table 2B
Examples of customer value metrics.

Author (year)	Finding/contribution
Venkatesan and Kumar (2004)	The authors define a customer-level CLV objective function and empirically identify the behavioral drivers of contribution margin and purchase frequency. In addition, the authors present an optimal resource allocation strategy that can be used by the firm to send the appropriate marketing communications at the right time to maximize profits.
Rust et al. (2004b)	The authors define financial return as a function of the change in Customer Equity as a result of an incremental increase in spending. The authors find drivers of Customer Equity based on survey information of customers from the Airline industry. In addition, the authors use a brand-switching matrix to introduce competitive effects into the model estimation.
Gupta et al. (2004)	The authors demonstrate how valuing customers makes it feasible to value firms, including high growth firms with negative earnings. They demonstrate their valuation method by using publicly available data for five firms. They find that a 1% improvement in retention, margin, or acquisition cost improves firm value by 5%, 1% and .1%, respectively. They also find that a 1% improvement in retention has almost five times greater impact on firm value than a 1% change in discount rate or cost of capital.
Petersen and Kumar (2008)	The authors introduce a new CLV objective function that includes product returns as a separate part of the equation. The authors show that the newly proposed CLV objective function provides better fit, better prediction, lower over-prediction bias, and better segmentation than previous CLV models. In addition, the authors show the firm requires fewer resources to maximize profitability when it takes product returns into account.

Brand equity

Many of the metrics that measure brand value or brand equity stem from the research of Keller (1993) who provides a conceptual model that outlines how to measure brand equity from the customer's perspective. Following this, many studies began to not only measure a customer's individual brand value or the firm's brand equity, but also began to link this measure to both customer equity and shareholder value. In most cases there have been positive links between increases in brand equity with increases of customer or firm value. For example, using brand values published in *Financial World* and Market-to-Book ratios from publicly traded companies, Kerin and Sethuraman (1998) found a positive, but decreasing returns, relationship between brand value and shareholder value. However their sample only included firms that were listed on the "Most Valued Brands" list. Using a list of brand values from *Interbrand* and market capitalizations from publicly accessible data, Madden et al. (2006) found evidence that increases in a brand's strength were related

to increases in shareholder value. This was done by analyzing the performance of different portfolios of companies – (1) World's Most Valued Brands (WMVB), (2) Reduced-Market (RM) – which contains all those firms in the Center for Research in Securities Market database (except those in WMVB), and (3) Full-Market (FM) – which contains all firms. However, there is still work to be done in this area. As Leone et al. (2006) points out, while there are some links between brand equity and customer equity, the literature exploring links between brand equity and customer equity is sparse. This gives a great opportunity for research to continue to develop methods to link brand and customer equity.

Customer value

There has been a significant amount of literature that has set out to develop metrics that measure the value of customers, whether it is at the individual level in the form of customer lifetime value (CLV) or at the aggregate level (customer equity). Up

Table 2C
Examples of word of mouth and referral value metrics.

Author (year)	Finding/contribution
Hogan et al. (2003)	The authors empirically show through surveys that losing customers through defection to a competitor or no longer using a product can have a great impact on the revenue stream across the life of the product cycle. This is due to the word of mouth effect that is lost when customers no longer advocate on behalf of the company.
Kumar et al. (2007)	The authors present an equation that measures the value of referrals for customers from a firm. The authors also show the results of an effective field experiment with a B2C firm where customers were targeted based on their CLV and CRV (Customer Referral Value) scores.
Villanueva et al. (2008)	Firms acquire customers through costly but quick investments in advertising and slow but cheap investments in building word of mouth. The authors find that in the short-term a firm can increase customer equity more using advertising. However, in the long-term the firm can increase customer equity significantly more with investments in word of mouth.
Kumar et al. (2008c)	The authors provide a straightforward four-step process for predicting Customer Referral Value (CRV). Then the authors run a series of three field experiments to determine the most effective marketing strategy for sending targeted marketing communications to customers based on CLV and CRV.

Table 2D
Examples of retention and acquisition metrics.

Author (year)	Finding/contribution
Thomas (2001)	The author shows that customer acquisition and retention are not independent processes. However, because of data limitations, customer management decisions are frequently based only on an analysis of acquired customers. This analysis shows that these decisions can be biased and misleading. The author presents a modeling approach that estimates the length of a customer's lifetime and adjusts for this bias.
Verhoef (2003)	The author investigates the differential effects of customer relationship perceptions and relationship marketing instruments on customer retention and customer share development over time. The results show that affective commitment and loyalty programs that provide economic incentives positively affect both customer retention and customer share development, whereas direct mailings influence customer share development. However, the effect of these variables is rather small.
Reinartz et al. (2005)	In this research, the authors present a modeling framework for balancing resources between customer acquisition efforts and customer retention efforts. The key question that the framework addresses is, "What is the customer profitability maximizing balance?" In addition, they answer questions about how much marketing spending to allocate to customer acquisition and retention and how to distribute those allocations across communication channels.
Fader et al. (2005)	The authors present a new model that links the well-known RFM (recency, frequency, monetary value) paradigm with customer lifetime value (CLV). The stochastic model, featuring a Pareto/NBD framework to capture the flow of transactions over time and a gamma-gamma sub-model for dollars per transaction, reveals a number of subtle but important non-linear associations that would be missed by relying on observed data alone.

to this point, the purpose of measuring CLV and customer equity has been for optimal customer selection in marketing campaigns and to measure marketing effectiveness post-campaign. Rust et al. (2004b) use survey results from consumers located in two different northeastern US towns to determine drivers of customer choice and customer lifetime value. In addition, they are able to project the return on marketing expenditures for different types of campaigns in each of the companies studied and account for competitive information using a brand switching matrix. Venkatesan and Kumar (2004) use a sample of B2B customers from a multinational high-tech firm to first determine the behavioral and demographic drivers of CLV. Then they determine an optimal resource allocation strategy using genetic

algorithms. The end result is a customer-level resource allocation strategy that maximizes each customer's lifetime value. Research in marketing is also beginning to identify linkages between these metrics and overall firm value. Gupta et al. (2004) use information from publicly traded companies to estimate customer equity and firm value. They find that as long as a firm is able to project its customer growth pattern and estimate its current customer margin that it is feasible to determine customer equity and overall firm value. This is especially important in situations where firms have short histories of transactions, are involved in a high-growth period, and have a negative cash flow due to early capital investments. Additional research by Kumar and Shah (forthcoming) was able to find a direct relationship

Table 2E
Examples of cross-buying and up-buying metrics.

Author (year)	Finding/contribution
Verhoef et al. (2001)	In this article the authors investigate how satisfaction and payment equity affect cross-buying at a multiservice provider. They also consider its competitors' performance on these factors. The results show that the effect of satisfaction differs between customers with lengthy and short relationships. It also shows that payment equity negatively affects cross-buying for customers with long relationships. However, if the prices of the supplier are perceived as fairer than the prices of the competitor, the customers' probability of cross-buying increases.
Knott et al. (2002)	The authors present and evaluate next-product-to-buy (NPTB) models for improving the effectiveness of cross-selling. The NPTB model reduces the waste of poorly targeted cross-selling activities by predicting the product each customer would be most likely to buy next. The field test shows that the NPTB model increases profits compared to a heuristic approach, and that profits are incremental over and above sales that would have occurred through other channels.
Kumar et al. (2006b)	The authors provide a framework that enables managers to determine the appropriate product(s) to sell to customers at a given time based on that customer's history and the history of other customers at the firm.
Kumar et al. (2008a)	The authors provide empirical evidence of the antecedents and consequences of crossbuying in a non-contractual retail setting.
Kumar et al. (forthcoming)	The authors provide a framework and methodology for targeting the right customers with the right products at the right time. They do this by running a field experiment with a company and comparing the results of a typical sales campaign with one that is driven by their methodology.

Table 2F

Examples of multi-channel shopping metrics.

Author (year)	Finding/contribution
Thomas and Sullivan (2005)	This article presents a marketing communications process that uses customer relationship management ideas for multichannel retailers. The authors describe and then demonstrate the process with enterprise-level data from a major U.S. retailer with multiple channels.
Kumar and Venkatesan (2005)	The authors develop a conceptual framework, which identifies the customer-level characteristics and supplier factors that are associated with purchase behavior across multiple channels. They also propose and empirically show that multichannel shoppers provide benefits as measured by several customer-based metrics.
Venkatesan et al. (2007)	The authors explore the drivers of multichannel shopping and the impact of multichannel shopping on customer profitability. The authors provide evidence that multichannel shopping is associated with higher customer profitability.
Pauwels and Neslin (2008)	The authors use a multichannel customer management perspective to assess the revenue impact of adding bricks-and-mortar stores to a firm's already existing repertoire of catalog and Internet channels. We decompose the revenue impact into customer <i>acquisition</i> , <i>frequency</i> of orders, returns, and exchanges, and <i>size</i> of orders, returns, and exchanges. The analysis estimates the net impact of adding the store channel was to increase revenues by 37%. The majority of this increase was due to an improvement in customer retention through higher purchase frequency.

between CLV and shareholder value. This suggests that if marketing managers can continue to run marketing campaigns to increase customer value that this will directly lead to increases in shareholder value. This research is only a start though. There is still a need to continually improve measures of CLV and to link CLV to financial outcomes.

Word of mouth and referral value

Ever since Reichheld (2003) suggested that the key to business growth lies in the positive word of mouth of a firm's customers, that is Net Promoter Score, research in marketing has started to explore this connection between word of mouth and customer/firm value. Initially, Hogan et al. (2003) were able to show the value lost over time when a customer disadopts or defects from a firm, using the Bass model for the diffusion of new products and a Monte Carlo simulation. This lost value was not only a function of lost purchases, but it was also a function of the lost word of mouth the customer spread about the product causing losses of potential future sales. Even more troubling to this finding is the fact that customers who are acquired via word of mouth are significantly more profitable in the long-term than customers who are acquired via advertising and promotion. Using data from an Internet firm that provided free web hosting

to its registered users, Villanueva et al. (2008) found that customer who were acquired using costly, but short-term marketing advertisements and promotions give fewer than half the profits of customers acquired using cheap, but long-term investments in word of mouth marketing. This makes it even more important to identify the customers who are valuable with regard to word of mouth and referral behavior and attempt to retain those customers. Additionally, a study by Kumar et al. (2007) using data from a financial services and telecommunications firm found that customers with a high CLV are often not the same as customers with a high customer referral value (CRV), making it is especially important to know which customers are spreading word of mouth. Thus, it is critical to not only measure the value of word of mouth and customer lifetime value, but also to continue researching ways to link additional metrics such as customer word of mouth and referral behavior to marketing strategy and then to financial performance.

Customer retention and acquisition

Increases in customer retention and acquisition are tenets to successful marketing strategies. However, firms need to be careful not to make decisions about customer acquisition and customer retention in isolation. Research by Thomas (2001)

Table 2G

Examples of product returns metrics.

Author (year)	Finding/contribution
Anderson et al. (forthcoming)	The authors show that not including product returns in the demand function creates an overestimation bias of demand. In addition, the authors empirically show that customers have an option value for product returns that is measurable.
Petersen and Kumar (forthcoming)	The authors use data from a B2C catalog retailer to empirically describe the antecedents and consequences of product return behavior. The authors find that product returns positively affect (to a threshold) future purchase behavior – making them necessary, but not evil.
Anderson et al. (2008)	The authors run a field experiment with a retail firm and empirically show that products offered on sale have a lower probability of being returned than products purchased at full price.
Petersen and Kumar (2008)	The authors integrate product return behavior in the CLV objective function and show that not including it or including it as a component of buying behavior (i.e., net buying behavior as products purchased minus products returned) offers significant decreases in predictive accuracy and optimal resource allocation.

used data from an airline pilot service organization and a latent-class Tobit modeling framework to show that customer acquisition and retention are inherently linked. Thus, the firm would never want to only maximize acquisition rates or maximize retention rates to maximize profitability since customer retention relies directly on which customers were acquired. This would only lead to acquiring and retaining customers who are not profitable in the long term. Instead, it is ideal to maximize profits from customer lifetime value (CLV) by simultaneously managing acquisition and retention of customers. Research by Reinartz et al. (2005) used data from a high-tech B2B firm which simultaneously modeled acquisition likelihood, relationship duration, and customer profitability. The authors found that it is necessary to quantify trade-off between investments in acquisition and retention in order to maximize firm profitability. Once we can understand the links between customer acquisition and customer retention, it is necessary to begin to link these metrics with some financial outcomes. Recent research by Fader et al. (2005) used data from CDNOW to link RFM (Recency, Frequency, and Monetary Value) to CLV using iso-value curves. Once a firm is able to start establishing linkages between RFM and CLV, the next step is to develop marketing strategies that can continue to use metrics like RFM to increase CLV. Research by Verhoef (2003) shows how establishing a series of direct marketing campaigns or even loyalty programs that build affective commitment and potentially lead to increases in future customer purchase behavior. However, the end result is that while some linkages have been established between customer acquisition, customer retention, and CLV, there are still significant opportunities for research in marketing to advance these measures and linkages.

Cross-buying and up-buying

Cross-buying and up-buying offer firms the chance to continue to increase revenue and profit contributions from current customers, since it has been shown that customers who cross-buy are more profitable than customers who do not (Kumar et al. 2008a). The difficulty in implementing strategies to effectively increase cross-buying and up-buying is in determining: (1) which customers are likely to crossbuy, (2) which new products those customers are likely to purchase, (3) what marketing message to send those customers, and (4) when those customers are likely to crossbuy. Recent research has started to address some of these issues. First, Kumar et al. (2008a) used data from a major catalog retailer to identify the drivers and consequences of customers who crossbuy in different product categories. Managers can use these drivers, such as average interpurchase time, to identify the ideal customers within the firm's database that would be most responsive to cross-selling and up-selling campaigns. In addition, consequences of crossbuying behavior included increases in contribution margin per order and number of orders. Knott et al. (2002) used a Next-Product-to-Buy (NPTB) model to assist a retail bank with identifying the customers who were likely to purchase a specific loan product. Finally, Kumar et al. (2006b, 2008d) use data from a B2B high-tech firm, a B2C financial services firm, and a B2C telecommunications firm provide a framework for targeting the right customers, with the right prod-

ucts, at the right time. The results show that when these three decisions are modeled simultaneously, managers can significantly increase their customer targeting accuracy. These studies, though, only provide results of experiments with a few individual firms. There is still a great opportunity for research to explore the effects of cross-selling and up-selling strategies on customer and firm profitability across different firms and industries.

Multi-channel shopping

Where it was less common in the past for firms to have a presence in multiple channels, with the advent of the Internet, almost all firms now have a multichannel presence. The challenge then is to understand how each of the channels can impact customer purchase behavior and customer profitability. First, research has shown that customers who shop in multiple channels are more profitable than customers who shop in only a single channel. Using data from a high-tech B2B firm, Kumar and Venkatesan (2005) show that customers who shop across multiple distribution channels are more likely to score highly on various customer-based metrics such as revenue and likelihood to stay active. In addition, Venkatesan et al. (2007) use data from an apparel retailer to show that customer who purchase across more distribution channels have a higher future profit potential. However, research is just starting to analyze how firms can develop a strategy to communicate with customers effectively in different channels. Thomas and Sullivan (2005) use data from a major US retailer to develop a six-step process of how to manage marketing communications with multichannel customers. Additional research by Pauwels and Neslin (2008) uses data from a major catalog retailer to quantify the impact of opening a brick-and-mortar retail store when the only channels the firm previously used was catalog and Internet. However, with the continuing growth of retailers across many different channels, several questions still remain. These research questions include how to effectively migrate customers to different channels or how to measure the impact of channels where no purchases occur, for example using the Internet for search and the brick-and-mortar store for purchase. This leaves ample opportunities for future research to develop metrics that measure the impact of multi-channel shopping on customer profitability.

Product returns

Up until recently many firms have seen product returns only as a necessary hassle of doing business and a drain on profits. However, recent research has shown that products returns do play a major role in the exchange process and customers who do return a moderate amount of products are, ceteris paribus, the most profitable in the future. Petersen and Kumar (forthcoming, 2008) used data from a major US catalog retailer to first show that customers who return from 10 to 15% of purchases purchase more than customer who return too many or too few products. The authors also showed that product returns are a key driver in the computation of CLV and firms that do not incorporate product returns directly into calculations of CLV will overestimate CLV and improperly allocate marketing resources. In addition, Anderson et al. (forthcoming) develop a structural model that shows that it there is an option value of product returns that

is measurable, suggesting that omitting product returns from an estimation of demand creates a bias and that it is possible to find optimal product return policies for different firms. This is mainly due to the fact that customers who have satisfactory product return experiences tend to purchase more in the future and have a stronger positive relationship with the firm. However, for firms to link a product returns metric to customer value and firm performance more research is needed to continue to identify the drivers and consequences of product return behavior. Currently, there are two studies which identify some of the drivers of product return behavior. Anderson et al. (2008) use data from a mail order catalog firm to compare varying cross-item and within item attributes and their impact on demand. One main finding was that the lower the price of the item the less likely the item would be returned. Additionally, Petersen and Kumar (forthcoming) empirically determined several antecedents of customer product returns, including variables such as cross-buying and multichannel shopping behavior. However, the sparse research on customer product return behavior still leaves a significant opportunity for future research to continue to build product return metrics that can be useful for managing customers for profits.

As a result of all of this research, there exist many different metrics for retailers to use to manage their customers. It becomes increasingly important for managers to understand how each of these metrics can be used strategically for short-term and long-term business goals, that is how short-term metrics are linked to long-term metrics and how both short-term and long-term metrics are linked to financial performance. To do so, managers need to also understand which metrics will provide relevant information about the past and the current financial position of the firm (backward-looking) and which metrics will help managers lead firms into the future (forward-looking). Next, we provide some discussion on the differences between backward-looking and forward-looking metrics and which metrics can be linked to future financial performance.

Backward-looking versus forward-looking metrics

Many marketing metrics used by firms currently are backward-looking, or at best present-looking, in nature (Zeithaml et al. 2006). Examples of backward-looking metrics include measures of customer satisfaction relating to past purchase experiences, measures of service quality relating to past service experiences, and measures of perceived loyalty that reflect the customer's perception of their own behavior up to the current time period. Many of these backward-looking metrics, along with several other operational and behavioral measures, are provided for easy viewing on a periodic basis (e.g., quarterly, monthly, weekly, daily, and even real-time) for top managers through marketing dashboards, see Reibstein et al. (2005) for a detailed description of marketing dashboards. These backward-looking metrics serve the purpose of helping marketing managers quantify the effectiveness of past marketing campaigns that provide a clearer picture of current firm performance. However, while these metrics can show managers why the firm is at its current state, these metrics have been shown to

offer little to no predictive ability to future customer behavior or firm performance.

More recently much of the academic research has focused on forward-looking metrics that offer some predictive ability about future customer behavior or firm performance (Kumar 2008b). These forward-looking metrics harness the power of past customer attitudes and behaviors to try and offer some predictive capabilities about future customer behavior and firm performance. As a result, many of the backward-looking metrics have been used as predictors of future customer behavior and firm performance. However, the results tend to be mediocre at best. For example, when firms measure customer satisfaction, by the time the data is received and analyzed, it reflects yesterday's perceptions of satisfaction. It also does not include any information about competitors' actions or potential customer prospects. All of these factors cause customer satisfaction to be a less than adequate predictor of future customer behavior or firm performance.

This has led to many new forward-looking metrics, such as customer lifetime value (CLV). Venkatesan and Kumar (2004) uses behavioral information about past customer interactions with the firm to predict future customer behavior and customer value. The authors use variables such as average interpurchase time and cross-buying behavior and relate these variables directly with future purchase frequencies and future contribution margins. In addition, these findings have led to research in marketing which has been able to account for competitive interactions with customers. Rust et al. (2004b) use a brand switching matrix and customer survey information to account for switching behavior among a set of customers. In an alternative method, Kumar et al. (2008c) impute each customer's competitive purchase behavior by analyzing deviations in each customer's average interpurchase time. With regard to customer acquisition, Reinartz et al. (2005) account for a prospect's likelihood to buy from a firm for the first time by comparing demographic profiles of prospects with those of current customers who are profitable. The end result of these forward-looking metrics, see Zeithaml et al. (2006) for a more complete list and discussion, has been to allow manager to more strategically plan effective marketing actions and better justify the spending of marketing resources on both current and potential customers.

Marketing metrics and firm value

Many of the metrics used by marketing managers can be split into to main categories: metrics that measure the value of brands and metrics that measure the value of customers. Many of the metrics related to the value of brands were the product of managers who wanted to quantify the intangible value of firms for purposes of mergers and acquisitions. Consequently, this spurred much research on brand value and brand equity (Aaker 1991; Keller 1993). Recently, there has been a call for research that links brand equity to customer equity and firm value (Madden et al. 2006). Additional research has also showed how to link an individual's brand value to that individual's customer value. Kumar et al. (2008b) develop a conceptual framework that first uses the components of an individual's brand value and

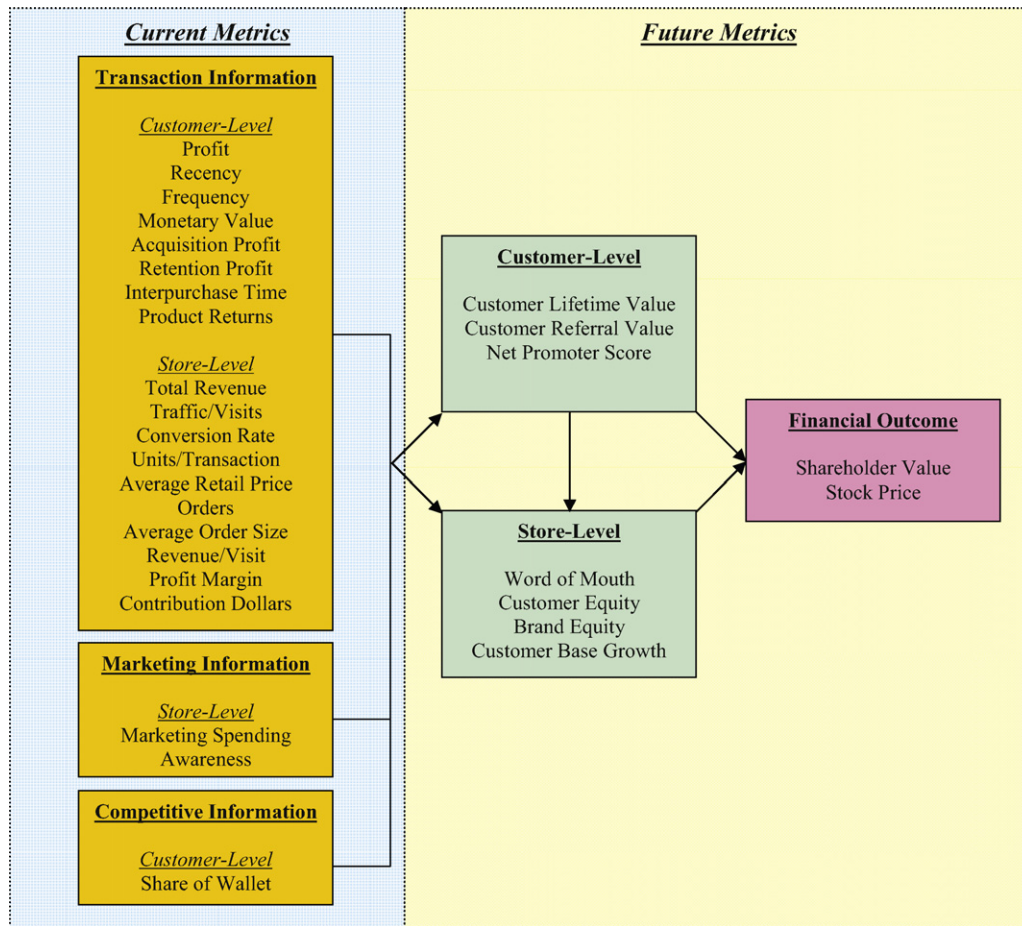


Fig. 1. Metrics we need to know.

links this value directly to behavioral outcomes such as purchase frequency and contribution margin. Then the authors link these behavioral outcomes with individual-level and firm-level firm strategies to enhance CLV and firm value. These studies have shown the importance of brand value metrics in their relation to customer and firm value. It also allows managers to justify marketing spend on increasing individual brand value and brand equity since they can directly measure the impact of brand value on customer and firm value.

There have been many different types of metrics that measure customers, from customer satisfaction to customer behavior. However, what seems to be a common thread amongst much of the research on customer metrics is that the end goal is to relate customer metrics to some form of customer value, for example CLV or customer equity. There is a significant amount of research that has been providing frameworks for linking marketing spend to customer value to firm value (Srivastava et al. 1998). Perhaps one of the biggest challenges to overcome in this area is the availability of data on customer and firm value. Only recently has research by Kumar and Shah (forthcoming) been able to empirically link CLV to shareholder value. The authors first calculate CLV and then link those values to a firm's stock price over time. This research is an important step for managers to show that marketing efforts are measurable and are directly related to firm value.

What we need to know

In Fig. 1, we organize the relevant metrics into four groups: at the customer and store levels for the current and the future. In addition, while the methods with which one estimates these metrics at the customer or store level (unit of analysis) and for the current and future (time period) may differ across the three key retail channels (online, catalog, and brick-and-mortar) giving rise to 12 cells (2 unit of analysis \times 2 time period \times 3 retail channels), we do not expect that the theoretical constructs themselves will differ across channels. Thus, we provide the metrics and their linkages in a single framework in Fig. 1. We break down the current metrics into three main categories: (1) transaction information, (2) marketing information, and (3) competitive information. We then provide some discussion on research that has started to link these current metrics with future metrics – both at the customer and store level. Finally, we discuss how these future metrics are linked directly to financial outcomes for firms.

Current value measures at the customer level

Profitability, of course, is an important metric with which to evaluate customers. A number of different approaches have been suggested to understand the drivers of the current level

of customer profitability. A number of these approaches have already been covered in the “Assessment of the Literature”. However, research needs to focus on metrics of profitability that are forward-looking. Research should not use metrics such as past customer value (PCV) which measures the past profit of a customer. Instead, retailers should consider several key measures that relate to future profitability. One is the popular “RFM” measures that report the time since the customer’s last purchase (recency), the frequency with which the customer makes purchases (frequency) and the amount a customer typically spends (monetary value). Each piece of the RFM measure has been shown to be a key driver in computing future customer profitability and recent research has also shown how managers can directly predict CLV by using each of the three inputs of RFM (Fader et al. 2005).

Similarly, understanding the acquisition rate and the retention rate can give guidance as to the current numbers of active customers. In addition, many firms use measures of “cost of acquisition” and “cost of retention” as guidance for which customers to acquire and retain. However, research has shown that it is not necessarily ideal to only focus on trying to acquire customers who are inexpensive to acquire and inexpensive to retain (Reinartz et al. 2005). Instead, it is important to understand that there are also profitable customers who are expensive to acquire, expensive to retain, or both. The key is determining which factors make different customers profitable to the firm. Thus, managers and retailers instead need to focus on metrics related to acquisition and retention that focus on acquisition profits and retention profits. In addition, these metrics should not be maximized in isolation. There is an inherent dependence between acquisition and retention requiring managers to determine spending on acquisition and retention simultaneously (Reinartz et al. 2005; Thomas 2001).

Past research has used past purchase frequencies to predict future purchase frequencies. However, it is rare for customers, especially in non-contractual settings to follow the same past purchase frequencies over time. Instead research needs to focus on methods to predict future interpurchase times to help describe expected customer buying behavior. Regularities in interpurchase times have been fruitfully modeled with a generalized gamma distribution. Allenby et al. (1999) use data from a major investment brokerage to model inter-trading times of investors. Additionally, Venkatesan and Kumar (2004) use a generalized gamma distribution to predict the interpurchase times of the customers from a high-tech B2B firm. Interpurchase times have also allowed researchers to impute potential competitive purchase behavior from customers. If a customer tends to follow a general purchasing pattern, it is possible for statistical models to uncover deviations in that purchasing pattern and attribute those deviations to purchases from competitors (Kumar et al. 2008a,b,c,d, forthcoming). Thus, research needs to continue to develop methods that can predict future customer buying patterns.

Product returns are a growing problem with obvious impact on a customer’s value, with the amount of product returns exceeding \$100 Billion annually (Blanchard 2007). However, research has shown that there can be some profitable benefits to

customer product returns. For example, customers who return a moderate amount of purchases, 10–15% in total, have been shown to on average purchase more into the future than any other customer. In addition, customer product return behavior has been linked directly to future customer buying behavior and CLV (Petersen and Kumar forthcoming, 2008). This is a key example where a metric commonly used for a different purpose outside of marketing, in this case in operations management for supply chain management, can be used by marketing researchers to establish linkages between current and future customer behavior.

Metrics that go beyond the retailer’s own database to shed light on a customer’s spending with competitor retailers allows the retailer to understand what “share of wallet” it is attracting. This leaves open the possibility that the retailer might focus on growing customer expenditure from those customers for whom the retailer currently has a small share of wallet and a large size of wallet. Du et al. (2007) use data from a major US bank with information about its customers’ account balances within and outside of the bank. The authors find little correlation between the volume of transaction within the bank and with other banks, along with the fact that a relatively small percentage of customers account for a large proportion of external transactions. This leaves opportunities for the bank to significantly increase value from customers with low share of wallet and high size of wallet. In addition, this analysis can also show that it might not be fruitful to spend significant marketing resources to encourage cross-selling and up-selling on highly profitable customers who are already spending their entire budget (100% share of wallet) and instead market to customers with potential – those with low share of wallet and high size of wallet. However, managers need to be sure not to just base strategic decisions only on a customer’s current share of wallet. Instead, research needs to focus on linking share of wallet and size of wallet with future metrics such as CLV by using share of wallet and size of wallet to identify the optimal set of customers for marketing campaigns.

Current value metrics at the store level

Revenue continues to be an important metric with which to evaluate stores. Two different models of store revenue were presented at the Conference on Customer Experience Management in Retailing at Babson College, April 24–26, 2008. Fig. 2 presents the model that Len Schlesinger (former COO of The

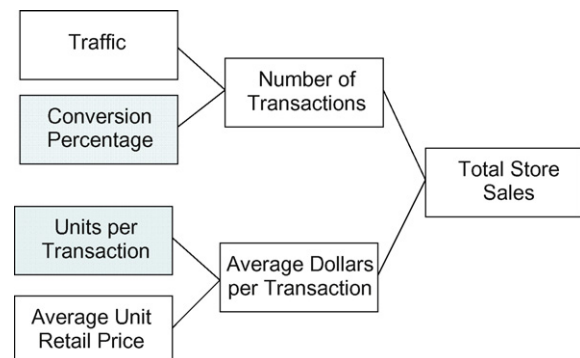


Fig. 2. The Limited’s model.

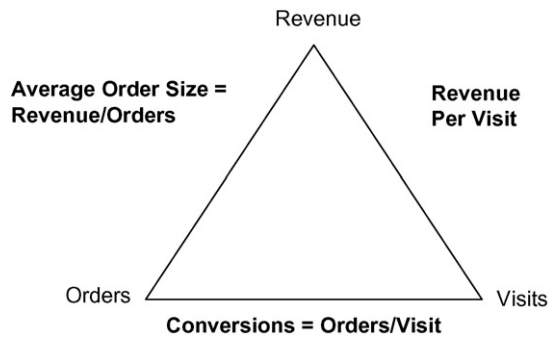


Fig. 3. Overstock's web analytics triangle.

Limited, now President of Babson College) reported having used to revitalize The Limited's brick-and-mortar stores. Breaking store sales down as described in Fig. 2 gave The Limited clear guidance about how to motivate store personnel. Traffic to the store was largely determined by attributes of the shopping center and the store's position in that shopping center. Retail prices were determined centrally. So incentives were designed to focus store personnel on the two shaded boxes: conversion percentage and units purchased per transaction. The end result was that these two metrics could be tied directly to future total store sales, which in turn could be directly linked to future firm profits and shareholder value. Thus, Schlesinger's experience suggests that key brick-and-mortar store level metrics should include traffic, conversion percentage, units per transaction and average unit retail price.

Also at that conference, Geoff Atkinson, VP of Tactical Marketing for Overstock.com (an online low price retailer) presented the model in Fig. 3. Atkinson suggested that many websites make the mistake of looking primarily at conversion percentage (as The Limited brick-and-mortar store did), which misses the importance of average order size. Overstock chooses to focus on revenue per visit as the primary metric of website performance since that metric takes both conversion and average order size into account. Overstock uses these metrics when comparing two or more variables and tracks the results using Omniture and several internal systems. Overstock measures site performance on these metrics daily and weekly. Trends in these metrics are used to evaluate website design improvements. Overstock's experience suggests that online store level metrics should include orders, revenue, visits, conversions, average order size and revenue per visit – similar to those in brick-and-mortar and other offline channels (e.g., catalogs).

In addition to the revenue focused metrics presented by The Limited and Overstock.com, we also need metrics linking store revenue to store profit. Such measures include marketing spending, profit margins, contribution dollars, and awareness of retail stores and specific retail brands. In general if we follow the hierarchy of effects model (*awareness, liking, trial, repeat, loyalty*), it is thought that raising awareness of the retail store or a given brand will eventually lead to an initial and potentially repeat purchase. In addition, if the store has a grasp on its profit from the sales of goods (profit margin and contribution dollars) and its ability to acquire and retain customers (effectiveness of marketing spend), with the general awareness of the store and

its products/services, then a direct link can be drawn to firm profitability and shareholder value.

Future value measures at the customer level

Virtually all measures of the important metric "Customer Lifetime Value" are built with historical data and hence reflect the customer's expected future value if nothing changes as the customer moves into the future. But, of course, things *will* change and some of those changes are under the control of marketers. There is need for forward-looking measures of a customer's expected lifetime value and those measures should include the impact of different marketing programs on that lifetime value.

Questioning Reichheld's (2003) work on a "net promoter score" (the percentage of surveyed customers who report that they are willing to recommend this company to a friend) led to exploring that a customer's value can be more than the value of the purchases that customer makes from the company as observed by Kumar et al. (2007). Specifically, Kumar et al. (2007) define a customer's referral value or CRV as the value of the business that a customer brings in minus the marketing costs that prompted that customer to make a referral. However, this research is just the beginning for metrics related to word of mouth and referrals. Research needs to continue to focus on the drivers of the value of word of mouth and its implications on customer and firm value.

Future value metrics at the store level

Positive "word of mouth", particularly as spread on the Internet, has been shown to be an important indicator of future success. Godes and Mayzlin (2004b) linked chat room comments to TV show ratings, Chevalier and Mayzlin (2006) linked online reviews and ratings to online book sales, and Dhar and Chang (2007) linked CD sales to blog posts and reviews. Measures of retailer-related online chat, reviews and blogs are relevant future value metrics at the store level. Research needs to continue to work on linking general word of mouth or 'buzz' about products to future sales. This way managers can predict the impact of a word of mouth marketing campaign is likely to have on future sales to determine the optimal level of investment.

A retailer's own brand equity, as measured by consumer surveys, should be related to the future value of the firm. As noted by Leone et al. (2006), one could also measure a retailer's brand equity as the sum of the customer equity (closely related to an aggregate measure of customer lifetime value) associated with each of the retailer's customers. On a related point, Leone et al. (2006) point out as well that the value of a manufacturer's brand to a retailer is not the same as the value of that brand to the manufacturer. In particular, the value of a manufacturer's brand to a retailer is related to the value, *to the retailer*, of the customers who buy that brand from the retailer. Thus, going forward research should focus on trying to link the increase of a firm or a retailer's brand value to a corresponding increase in total sales. Further, it is also important for some firms to identify an individual's brand value (IBV) and relate that IBV to

that customer's lifetime value (Kumar et al. 2008b). Then the firm can also make strategic decisions to build brand value and in turn customer value at the individual level through targeted marketing campaigns.

Just as we noted that share of wallet is an important customer level, current value metric that requires data beyond that found in a retailer's CRM database, "growth of the retailer's customer base" is a store level, future value metric that requires data beyond that in a retailer's CRM database. In order to grow a store's customer base, the retailer needs information about consumers who are not currently shopping at the store. With this information a retailer can compute its share of customers across the industry or in the marketplace and also identify the best prospects to target in order to grow the customer base. There are significant challenges to gathering data across all firms in an industry or even to gather panel data from a large sample of customers. However, it is still necessary for managers to understand what factors impact a growth in their customer base – whether it includes customers that switch from one company to another or whether it includes new customers who have never purchased in a given product category. Either way, research has to continue to develop methods for predicting a firm's growth in its customer base.

Finally, the ultimate store level, future value metric is a financial outcome: shareholder value or stock price. The market's expectations about the future of the firm are impounded in a firm's shareholder value or stock price. It would be particularly useful to develop an understanding of the factors that influence a retailer's stock price. In other words, what are the current/future and customer/store level metrics that can be linked to a retailer's stock price and in turn how can these metrics be strategically used to increase a retailer's stock price? To this point few studies have been able to build links between marketing metrics and shareholder value or stock price, with few exceptions (e.g., Kumar and Shah forthcoming). However, there are still ample opportunities to continue to develop these linkages, especially since it is often necessary for marketers to continue to justify their resource allocations with empirical evidence showing the impact of their decisions.

How do we get there?

As noted earlier in this paper, it is critical to develop metrics in twelve "cells" of activity: at both the customer and store level and each with implications for both the current and the future time period. Then, each of those cells must be measured for the three key channels – online, catalog, and brick-and-mortar. An immediate question is how do we obtain the data necessary for these measurements? There are immediate challenges that are faced by both researchers and practitioners when developing and implementing marketing strategies based on metrics that are directly linked to customer value and firm performance. First, firms need to be able to capture the appropriate customer and marketing data to even develop measures for different metrics. Then, managers and academics alike need to determine how to operationalize these variables so that they can be used effectively. This can only be done when the firm captures data

at relevant intervals of time. Managers then need to properly track the incoming data and the effectiveness of marketing programs to continue to develop new programs. Next, it is crucial to use this data to build field experiments to test the effectiveness of these predictions. Finally, it is necessary for these firms to disseminate this knowledge within firms to gain buy-in from not only marketing and sales, but also from top management. Only then can marketing justify its position within the firm. We discuss each of these points in detail below.

Data capture

Let us assume that we can use the basic data obtained for both current metrics and for forecasting, extrapolation into the future, or both. This implies that we need measures from the three channels at two levels of aggregation. To take measures at the customer level implies that the firm must have an information system in place to systematically track and capture that information. Consider the online case. There is a considerable amount of data generated from online behavior but only purchase data can be captured longitudinally.¹ Brick-and-mortar channels only permit longitudinal data collection through devices like super-market panels which address a very small sample of consumers. The best data are obtained from catalogs where it is relatively easy and customary to capture customer-level data. Ultimately, these data can then be aggregated to the store level. However, take the instance of a firm that desires to implement a CRM system to capture data about current and potential customers. Research suggests that about 70% of CRM system implementations fail in improving the bottom-line. How might a firm create a successful approach to capturing data? Much of the success of technology adoption in a firm comes from a firm's willingness to develop an incentive structure based on CRM usage and performance and the willingness to initiate, maintain, and terminate relationships with customers based on the recommendations of the CRM system (Krasnikov et al. 2008; Reinartz et al. 2004). Thus, it is important for firms to not just begin to collect data about customers, but to adopt data capture technologies that are aligned with the incentive structure of the firm.

Operationalization

Then once the data is collected, the next task is to identify how each of the metrics will be operationalized. In simpler cases, metrics such as profit at the customer level can directly mean how much profit a customer has provided the retailer in a given time frame. However, many metrics are much more difficult to operationalize. We only need to look at metrics such as customer satisfaction and customer loyalty to see the issues of metric operationalization. How should a firm operationalize a metric such as loyalty? We could define loyalty any number of ways. First, in terms of behavioral loyalty, it could refer to customer tenure, or the length of time since the customer made a purchase. It could

¹ Considerable progress is being made on "behavioral targeting" which permits search behavior across web site visits to be captured, but these data are not typically added to a customer's data file.

also be defined as the number of times a customer has purchased from a given firm. Finally, it could also be a combination of several metrics, such as an RFM score. In addition, loyalty could also be attitudinal. Firms could measure loyalty through surveys as the perception of the firm in the eyes of the customer. Also, other metrics which may seem straightforward to measure, such as product returns, can give different implications to managers based on their operationalization. For example, a recent study showed that three different operationalizations of product returns – (1) number of product returns, (2) value of product returns, and (3) ratio of products returned to total products purchased – gave three different conclusions to managers. This is a major problem when marketing managers try to link marketing metrics to financial performance. In different cases, different variable operationalizations provide vastly different results. This makes it extremely important for marketers to begin to standardize a single method of measuring each metric and to always use that method when linking a metric to a financial outcome. This can increase the validity of the measure and also allow for comparisons of metrics across firms, across research studies, and across time.

Measurement interval

Another relevant issue is the measurement or data interval. The appropriate interval should be matched to the product category. For frequently purchased products, weekly measures are appropriate. While not all customers purchase every week, it is critical particularly for the store-level measures to have short measurement intervals. This also permits the analyst to develop the best measures for the metrics describing future behavior. For durable goods or other products/services purchased less frequently, weekly data are probably unnecessary. In any case, the measurement interval should always be less than the average interpurchase time in order to account for heterogeneity in purchasing across consumers. A main issue that arises out of different measurement intervals occurs when different departments of a firm capture and measure data at different intervals. For example, take a large multi-national CPG company. It may be the case that this company measures sales across all stores on a weekly basis. This company may also measure advertising and other marketing spend on a monthly basis. Finally, this company may measure changes in distribution of products on a quarterly basis. Take another example of a high-tech B2B firm. This high-tech B2B firm collects information about sales to customers on a monthly level, but keeps information about marketing expenditures to customers (e.g., sales calls) as they occur. Thus the question is: Which level of time aggregation should be used for a longitudinal study? Should the firm aggregate the data to the monthly quarterly level and lose the variability of the weekly or daily transaction data? The problem here is a loss of variance in the more frequently measured data due to aggregation. Or, should the firm bring the quarterly or monthly data to the weekly or daily level by using average weekly or daily values for marketing and distribution data? The problem here is that the firm may not gain the full picture of the purchasing or marketing cycle by tracking it too frequently. In addition, the correct answer

to both questions may depend on the research question that we are trying to answer. To avoid this problem in the first place, firms need to consider appropriate data measurement intervals and capture data across all facets of the business at those intervals most appropriate for the products and services being sold.

Tracking

A basic level of analysis is tracking the metrics. While this does not show relationships between metrics, two-dimensional visual representations (metric over time) can stimulate discussion about the causes of a particular up or down trend. In addition, tracking is easy to communicate to senior management and throughout the organization. However, absolutely crucial is going beyond tracking to develop analyses that link marketing activities and the metrics. This gives the company the ability to allocate resources over marketing programs that will provide the greatest leverage in expanding the particular metric. For example, if the metric is customer lifetime value in the catalog channel, linking number of catalogs sent to a customer's CLV aids in the determination of the optimal number of catalogs to mail to each customer. Venkatesan and Kumar (2004) used data from a high-tech B2B firm to track the frequency and timing of different types of marketing communications and their impact on a customer's decision to purchase. This gives the firm an understanding of how decisions to allocate resources to customers are likely to affect a customer's decision to purchase in the future. Similarly, if the metric is at the firm level such as market share or excess stock price returns, companies can evaluate the impact of programs such as R&D, branding, and so forth on these metrics. Measuring alone is insufficient – developing models and establishing relationships between “inputs” and “outputs” is essential. How can this be done? A recent study which won the Marketing Science Practice Prize competition in 2003, exhibits exactly how a German catalog company successfully tracked its marketing communications over time to optimize catalog sending to customers (Elsner et al. 2004). The authors used a dynamic multi-level modeling approach with the elasticities of catalog mailing along with segmenting customers using RFM scores to determine optimal catalog mailing practices. This led the catalog company to go from the 5th to the 2nd market position.

Similarly, it is important to develop relationships between the metrics themselves to see if there are “sufficient statistics,” that is, measures that are highly correlated with others implying that the dashboard can be smaller. For example, firm-level metrics such as profitability and share price should be highly correlated. In addition, it would be useful to know if a particular metric is a leading indicator for another. For example, changes in brand equity should lead changes in sales, market share, or both.

Experimentation

The tracking and linking analyses just described are essential parts of a metrics program. However, a very useful step beyond these is to run controlled field experiments where the manager manipulates some aspect of the marketing program and monitors how it affects a selected metric. Particularly, amenable to

experimentation are the online and catalog channels. The latter has been the subject of experimentation for many years, the former since the inception of the Web-based channel. For example, a clothing retailer that uses both a catalog and an Internet site might be interested in seeing the impact of changing the merchandise mix or pricing on sales. The company would randomly selected customers who either visit the Web site or receive a catalog and offer the changed merchandise or price and keep another group as a control. Given the availability of customer-level data, however, the impact of the policy change on CLV could also be determined. While this can be done in a brick-and-mortar channel, it is much more difficult to implement given the need to coordinate over stores and measure the impact at the customer level (at least for the CLV metric). However, there is limited research in marketing that deals with direct experimentation. We first see experimentation in marketing research [Eastlack and Rao \(1986\)](#) with the Campbell Soup company. However, since that time, there have been few studies that have conducted actual experiments with firms. An example of a more current field experiment includes [Kumar et al. \(2006b, 2008d\)](#) where the authors used data from a high-tech B2B firm and B2C telecommunications and financial services firms to guide salesperson decision-making. While it is more difficult to publish studies that deal with experiments, it is much needed and can take care of many confounding factors.

Dissemination

From an organizational perspective, it is important that key metrics be disseminated throughout the company. Employees should be aware that senior management is very interested in both company- and customer-level metrics as it not only gives direction for data collection, but also demonstrates that management is seriously interested in its customers. There is also a rationale for “common ground” in that all managers need to know how their brands are being evaluated. Thus, there is a serious signaling effect that communicating key metrics has in the organization. Employees who own stock in the company are used to tracking the share price daily; they should also get used to tracking the key metrics at their desks.

Most companies are trying to do the communication throughout the organization through the use of a dashboard. This allows senior management the ability to indicate what are the important measures that all within the organization should be looking at in common ([Pauwels et al. 2008](#)). It has been reported that the McDonald’s CEO used to have the corporate dashboard strategically placed behind his desk. As such, anyone that came in to meet with him was looking at the CEO AND the dashboard. It was a strong message of what was important and what was being viewed by the top of the organization. A dashboard further keeps everyone up to date on the status of the brand/firm. One could view the dashboard in the form of a tree structure – there are the key output measures, as discussed previously, and then the drivers of each of these measures. As one gets further down the organization it is possible to “drill down” on each of these measures and understand the causal factors. For example, shareholder value is a key output measure and CLV being a driver.

Then, the question is what drives CLV? That would be acquisition, purchase amount, purchase frequency, and retention. We could then look at what marketing actions tend to drive each of these components. As can be quickly seen, with multiple output measures, and most actions affecting multiple drivers, the complexity starts to proliferate.

Linkages

Ideally, the linkages between drivers and output variables need to be well understood, and hopefully, empirically determined. Unfortunately, these relationships are not all well known. In part, this is because of the lack of data, and in part, because they are not all in the same place. In the absence of data driven relationships, judgmental parameters are necessary, often via decision calculus. Ironically, it is often the case that managers do not feel comfortable specifying their own judgment, yet have to make decisions based on this judgment all the time. If we can get the judgmental or empirically based relationships established, then it would be possible to continually experiment and update the relationships of these linkages. Some companies are very good at constantly experimenting, while others are not. However, without continual experimentation, these linkages cannot be well established or well understood.

The best place to start is by specifying the marketing objectives. Each retailer will have their own objectives. Getting alignment on the objectives is always a critical, and not necessarily, an easy step. The next step is to establish hypotheses of what are the drivers. Only then does it make sense to estimate the relationships. [Reibstein et al. \(2005\)](#), discuss the five steps in developing such a dashboard which include:

1. Selecting the key metrics
2. Populating the dashboard with data
3. Establishing the relationships between dashboard items
4. Forecasting and “what if” analysis
5. Connecting to financial consequences

In this article we have provided much of the material necessary to help managers develop a marketing dashboard for their firm. We have provided an assessment of the metrics that exist and those metrics which are necessary to monitor. We have provided guidance as to how firms can overcome the common challenges of migrating to these new metrics and capturing and tracking this data over time. Finally, we have shown which metrics have been shown to provide linkages to financial outcomes such as CLV and shareholder value. However, this research still needs to continue to refine the selection and measurement of marketing metrics and continue to develop linkages between marketing metrics and financial performance. Only then can marketing justify its place in the board room.

Guidelines for future research

Ongoing research on marketing metrics will continue to provide insights to marketing managers as they establish optimal marketing strategies which are directly linked to financial

outcomes. Thus, we provide a roadmap of much needed research in the area of marketing metrics. First and foremost, research needs to continue to establish the linkages between marketing metrics and firm performance. Next, research needs to continue to focus on the two tenets of marketing – customer acquisition and customer retention. In addition, marketing is constantly evolving and managers need to understand how “new” marketing, such as social content, can impact current marketing practice. Most importantly, the emphasis on these studies should continue to focus on metrics that can guide future decision-making and not focus only on the past. Finally, there needs to be a focus on research that relates directly to retailers, both in the measurement of retailer brand value and retailer market capitalization. Too often research is focused at the firm-level giving retailers few insights about strategic marketing decisions. We discuss each of these calls for new research below.

Establishing linkages

While we have outline the taxonomy cells for retailer metrics, there is much work which remains ahead. The American Marketing Association ran a conference in Atlanta in July 2008 for the Knowledge Coalition. This first endeavor of its sort was to establish what we know, in research and in practice, about the relationships between marketing spending and marketing results. The result was that much more work still needs to be done in this area. Too often when a company comes to cut a budget within an organization, marketing is cut off first. Often this is because marketing is unable to establish empirical linkages between marketing metrics, such as awareness, and financial outcomes, such as stock price. Thus, it is crucial that marketing managers begin to not only use their intuition to drive marketing decisions, but to also empirically link marketing metrics to financial outcomes. Then it will become easier to justify the need for marketing resources and also quantify both the negative short-term and long-term impact of a reduction in marketing resources.

Customer acquisition and retention

We also know that customer lifetime value is an important metric for retailers as well as others and that the sum of the customer lifetime values of all customers is customer equity. All firms strive to grow customer equity over time. This effort can only happen when resources are spent on trying to retain current profitable customers and to acquire new profitable customers. Some research has empirically shown that it is necessary to balance this acquisition and retention budget (Reinartz et al. 2005; Thomas 2001), however continual work is needed to better understand what drives customer acquisition and retention. Only then can marketing managers leverage the drivers of acquisition and retention to continue to grow each customer’s lifetime value and overall customer equity.

Social content

A new emerging field, and still not well known, is the impact of social content, such as product and store reviews, and blogs

(Godes and Mayzlin 2004a,b). Bizrate.com, Shopzilla.com, and Shopping.com all were established to provide user feedback to future shoppers about retail shopping sites. There is now the continual growth of such websites such as Bazaarvoice.com that empowers retail customers to help inform future shoppers. Many firms have turned to these forms of “new marketing” to try and grab a firm hold on the emerging trends. However, it is still unclear how firms can learn anything from these new media or even use these new media in predictive customer behavior and in turn firm profits. The impact of such social networking is needs to be better understood and provides many opportunities for future research.

Relating current actions to future actions

The big question facing marketers today is the impact of their current behavior on future performance (Zeithaml et al. 2006). It is often hard to use any current metrics to predict future performance. Most measures are short-term, and certainly drawing the link is easier when actions and results are contemporaneous. The question we are still in need of better exploration is the long-term impact of marketing actions. Thus, future research needs to begin to identify potential metrics that have the ability to predict future events (beyond just CLV and customer equity) to some degree of accuracy so that managers can track these leading indicators to get a better grasp on where the firm is heading – or even any interventions that are necessary to continue to increase firm value.

Retailer brand value

Marketers for years have been focused on brand establishment. Retailers have brands of their own, as well. There has been very little research that has focused specifically on the establishment of retail brands, whether these are specific products with a retailer’s brand name (Kumar and Steenkamp 2007) or the brand equity of the name of the retail store. One question is the impact of the brands that a retailer carries and its impact on the retailer’s brand itself. Future research needs to help quantify retail and private label brand values so that managers can make more strategic decisions to increase firm value.

Retailer market capitalization

Lastly, the ultimate is drawing the link between marketing spending and market capitalization. While some work has begun for manufacturing firms, little has been done for specifically for retailers. Given the increased complexity of real estate, and its fluctuating value, do the same principles hold for retailers as what has been found to date for manufacturers? This is another great opportunity for future research to investigate.

So, while progress has been made, there is considerable work still to be done to better understand the role of retailer metrics. In summary, this article has identified the directions retailers and manufacturers can take to not only build a profitable customer database, but also focus on building the brand value/equity through establishment of superior marketing metrics.

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