A service effort allocation model for assessing customer lifetime value in service marketing

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Abstract

Purpose – The purpose of this paper is to apply customer lifetime value models to assess the overall value of the service encounter and to establish implications that such an assessment has for managing customer relationships under a fixed-size salesforce.

Design/methodology/approach – Using a specific relationship between customer servicing activities and the buying rhythms of customers, an analytical model for assessing the overall value of a service encounter is developed.

Findings – A stochastic parameter is identified, characterizing the level of quality to compute the long-term value of a given customer and stochastic ordering properties to determine the relative value of different customers.

Research limitations/implications – The implications discussed are analytical to help service managers shaping their thought process in decision making. Future research can empirically test the model proposed.

Practical implications – The theorem specifies the optimal solutions to determine: how much capacity should be committed to a given customer; and how to choose a customer in the first place. These are important and useful tools for managers in making their managerial decisions in service marketing.

Originality/value – A general model of resource allocation is provided, under which those seminal models such as CALLPLAN, DETAILER are special cases. This is particularly valuable as key account management has become more important in globally operated businesses.

Keywords Services marketing, Customer services quality, Value chain, Resource allocation, Customer relations, Profit maximization

Paper type Research paper

An executive summary for managers can be found at the end of this article.

1. Introduction

As reported by Syntex Laboratories, Inc., a decision calculus model for salesforce size and deployment recommended a large change in the allocation of its salesforce to market services and, in financial terms, resulted in increases of $25 million (Lodish et al., 1988). Indeed, the relationship between salesforce allocation and profits achieved through service quality provided continues to be a vitally important issue. This is evidenced by comments of industry representatives attending a recent sales consortium that a major concern of sales managers is the management of their salesforce to effectively service diverse customer groups, in turn, to achieve the bottom-line efficiency and profitability (cf. Siguaw et al., 2003).

In the service profit chain, the classification of service quality along two dimensions, output/results and process experience, and the eventual link between service quality and firm profit (via customer value) primarily is presented in the context of the delivery of tangible products (Heskett et al., 1990). However, the concept lends itself to the possibility for competitive advantage even for the providers of services. Consider the case of a standardized product and market-determined prices. In such a case, the product itself (and its price) would be indistinguishable among sellers of the product. Consequently, from that perspective, customers would be indifferent from which firm they made their purchases. However, sellers still could differentiate themselves based on the service quality of the process by which the product was purchased.

In this paper, we focus on this angle of differentiation by developing an analytical model of the service encounter, which we define as the totality of a given customer’s multiple purchasing experiences.
intrinsic quality of the core product to play a role in persuading customers to choose one firm over another. As a consequence, in our model, customer value reduces to a function of a single argument, namely, the quality of the service encounter.

The remainder of this paper is organized as follows. In Section 2, we provide the background of our model and review the related literature in salesforce allocation. In doing so, we provide a general framework for modeling service effort allocation through salesforce allocation problems, which we use to identify features that distinguish our model from previous works. In Section 3, we develop a dynamic program for calculating the lifetime value of a given customer type, given a fixed salesforce capacity. We also provide the solution to the dynamic program and identify analytical properties. In Section 4, we apply these properties to address the two key managerial concerns identified earlier: How much capacity should be committed to a given customer type? And, which customer type should be given priority in terms of committing capacity? Finally, we conclude the paper by discussing the managerial implications and the limitations of our model in Section 5.

2. Model background and related research

Customer value and firm profit are inextricably linked by a reinforcing relationship that often is endogenous to the firm through updating of customers’ experiences and perceptions – this is the cornerstone of contemporary thinking in service marketing management. The idea is that customer relationship management designed to provide increased value to the customer ultimately yields a lifetime value to the service provider. The reason is because higher customer value increases customer satisfaction; thereby instilling customer loyalty; which, in turn, creates higher profit due to increased volume resulting from repeat purchases and positive word-of-mouth (Liu et al., 2000). In this paper, we propose a specific relationship between customer servicing activities, the buying rhythms of customers, and lifetime value. Although we focus on the optimal allocation of a particular resource, namely salesforce effort (e.g. time and strengths input to the customers) to provide services, the fundamental premise that customer lifetime value is, to a considerable extent, the outcome of a controllable management process as opposed to an exogenous parameter is a useful way of thinking about the allocation of resources in general. Yet, analytical models exploiting this approach still appear to be underrepresented in the scientific literature.

The notion of lifetime value represents a fundamental component of a more systems-oriented management framework coined the service profit chain (Heskett et al., 1997; Heskett et al., 1994). In brief, the service profit chain concept dictates that a firm that invests in its employees by providing overall internal quality of work life (for example, by recognizing and rewarding employee capabilities) should expect satisfied and loyal employees. This, in turn, increases productivity, which gives the firm greater leverage to provide value to the customer and consequently, leads to higher profit in the long run.

In focusing on the link between customer value and firm profit, the key is the notion of value, which in general terms, is defined as the ratio of the overall benefit received to the overall cost incurred. Thus, customer value can be expressed as service quality (service price (Heskett et al., 1990). This formalism is consistent with the theory of total quality management, which includes the precept that the definition of quality is dictated by the customer (often as a function of a stated price) and thus, quality can be designed into the service if the customer is consulted at the onset (Hauser and Clausing, 1988). From the customer’s perspective, the aggregate level of quality of a service is determined by the service’s fitness for use (Juran and Gryna Jr, 1980). For goods, fitness for use corresponds to a compilation of measures among a number of distinct dimensions of quality including performance, features, reliability, durability, and aesthetics (Garvin, 1987). For services, analog dimensions of quality include reliability, responsiveness, assurance, empathy, and tangibles (Zeithaml et al., 1990). In the context of the service profit chain, this same precept holds; but the dimensions of service quality are aggregated into two general dimensions: the intrinsic quality of the service itself; and the customer’s overall experience associated with the purchase of the service. In other words, the two broad dimensions of service quality are such that one dimension captures “what” the customer purchases in terms of output or results, and the second dimension captures “how” the customer perceives the process through which the purchase occurs.

To incorporate these in our model, we define a salesforce as an organizational entity responsible for interfacing with a given customer throughout the purchasing process. Thus, a firm’s salesforce, through its contact time with a given customer, establishes the overall purchasing experience for the customer. Accordingly, we use salesforce effort as our measure for the quality of the service encounter. Hence, in this paper we use salesforce effort and service effort interchangeably. We assume that salespersons are homogenous so that a customer’s perception of the service encounter does not depend on the level of a given salesperson’s “people skills.” In practice we can move toward this homogeneity through effective training. Increased sales effort provided over time to a single customer is interpreted by the customer as better service quality, and hence better value, which results in higher long-run profit. Unfortunately, however, sales effort is a limited resource. Indeed, there is a cost associated with increasing the aggregate amount of sales effort available, which very well may outweigh the higher long-run profit attributed to assigning unlimited effort to a given customer. We control for this simply by assuming a fixed-size salesforce, thus implying an imputed cost for the effort. The core research questions then are to determine:

- the long-term value to the firm associated with a constrained amount of aggregate sales effort available through which certain service level can be delivered, given that such effort is allocated optimally over time to the customer; and
- the implications on salesforce capacity planning and on customer segmentation and selection.

Based on interviews with managers and consistent with the dynamics of the GAPs Model of Service Quality (Zeithaml et al., 1990), it is apparent that customers differ along two key dimensions. First, customers differ in terms of their initial expectations regarding the level of service (hence the amount of sales effort) that they think they should receive. And, second, customers differ in terms of how they update over time their initial expectations in light of the service level (hence the sales effort) they actually receive; namely, customers differ in terms of the weight attached to the most recent service encounter relative to the weight attached to the
Cumulative experience over the relationship (Boulding et al., 1993; Hamer et al., 1999). These differences in customers could be associated with, for example, corporate culture, national culture (e.g. longer-term vendor-seller relationships often prevail in Japanese cultures (Hall and Hall, 1987; Money et al., 1998)), or personnel turnover rates in either or both of the buying and selling firms. More specific empirical research would be of value in identifying secondary variables that could be measured and calibrated to quantify the respective differences between specific customers.

Given the differences between customers, it is useful to categorize customers on the basis of their differences before allocating sales effort to them. Then, given a fixed sales capacity, we could determine the potential lifetime value of a given customer type associated with the available capacity. This essential calculation provides an important source of information to managers charged with allocating service effort through sales capacity. In particular, it provides insight for two parallel questions: first, how much capacity should be committed to a given customer type? And, second, which customer type should be given priority in terms of committing capacity? Our approach to the problem of service effort allocation through sales effort allocation aims to maximize long-term profits by balancing the lifetime value of a customer with capacity utilization.

The more recent management science treatment of sales effort models can be traced back to a 1971 special issue of Management Science in which three seminal papers were introduced: CALLPLAN (Lodish, 1971), DETAILER (Montgomery et al., 1971), and GEOLINE (Hess and Samuels, 1971). Since then, most of the work in this area has been some type of extension or combination of one or more of these three fundamental models (e.g. Parasuraman and Day, 1977; Parsons and Abeele, 1981; Lodish et al., 1988; Rangaswamy et al., 1990; Skiera and Albers, 1996, 1998; Drexl and Haase, 1999; Darmon, 2002; Yi et al., 2003). These three models are considered foundational models in Vandebosch and Weinberg’s (1993) comprehensive review on 18 sales effort models selected from 47 articles found in a five-year search of the ABI-INFORM database for five leading journals in management science. Of these three base models, GEOLINE is a territory assignment model. On the other hand, CALLPLAN and DETAILER are resource allocation models, which are central to the theme of this paper.

As reviewed in their comprehensive literature review, Vandebosch and Weinberg (1993) reported that:

CALLPLAN addresses a key personal selling question: How should a salesperson’s time be allocated between customers and prospects in his/her territory? The model provides an interactive call-planning system which is implemented at the individual sales representative level and is used to establish call-frequency norms for both customers and prospects.

This model is at the root of many salesforce operations models because it develops a simple yet powerful procedure for estimating sales response to effort. In addition, the modeling framework lends itself well to implementation and has an impressive track record of successful applications. For example, a controlled field experiment was conducted at United Airlines (Fudge and Lodish, 1977). In the experiment, ten salespersons used CALLPLAN to develop call-planning schedules while ten others did not. After six months, the CALLPLAN group achieved a significantly higher level of sales increases than the control group. As a result of this initial success, United Airlines continued to use CALLPLAN for several years. Another example of successful application achieved sales increase of $25 million for Syntex Laboratories, Inc. as cited in the beginning of this paper (Lodish et al., 1988). Thus, CALLPLAN is proven to have significant contribution to the practitioners in various industries.

However, this model is limited to addressing the problem of allocating a salesperson’s time across accounts or customers while many sales representatives market a product line and also need to decide how to allocate their effort across different product items within the product line they carried. Also, CALLPLAN is a static model for one period decision making. At best, it can be used for multiple periods with each period as an independent decision planning horizon separately. Such a nature makes it difficult to be applied to industries requiring cumulative sales efforts over time before a sales response may be achieved. Pharmaceutical industry is one industry among others requiring such cumulative efforts (cf. Vandebosch and Weinberg, 1993).

Contrast to CALLPLAN, DETAILER presents an alternative form of allocation model. The model considers the situation in which the salesperson markets a number of products and addresses the problem of allocating selling time or effort across products rather than customers. It also incorporates dynamic effects by assuming the sales response for a particular product to be a function of accumulated exposure to sales efforts carry over previous time periods. The dynamic feature enabled managers to test alternative sales effort policies (e.g. pulsing vs constant level of effort). Besides, like CALLPLAN, the model is relatively simple to apply and has been successfully implemented in multiple settings. Although one of the key features of DETAILER was the incorporation of time dynamics, regrettably, modeling of the time dynamics of changing sales effort allocations has not been actively pursued. Though the problem could be formulated as a dynamic program, the authors suggested a heuristic approach to incrementally improve the sales effort schedule. Thus, as models developed, this dynamic feature was dropped from most models in resources allocation area. Instead, recent models focus on sales results in a future period – or planning horizon – when the optimal allocation has been achieved. While most authors are careful to point out the limitations inherent in such an approach, the profit opportunities in dynamic strategies have not been adequately considered (cf. Vandebosch and Weinberg, 1993).

Like building long-term relationship over time in relationship marketing, service marketing often requires cumulative efforts to build up customers’ positive overall service perception hence behaviors through repeated service experiences. Among various ways, we propose to build service quality through optimal cumulative sales efforts which is one of the key contributions this paper attempts to make. Therefore, for the existing sales effort allocation models to be useful in service marketing, the dynamic feature must be actively pursued. In addition, given various possible responsibilities salespersons have in today’s market, they need decision tools that are more versatile than those for specific purpose in existing models. For these reasons, we offer a general framework for modeling service effort allocation through dynamic salesforce allocation problems and demonstrate that CALLPLAN and DETAILER are special cases of this framework each with its advantages and limitations. In the context of this framework, we provide a brief review of the basic concepts and results attributed to
CALLPLAN and DETAILER. Then, we identify the distinguishing features of our model.

The essential research question in salesforce allocation models is to determine the optimal allocation of a constrained resource across entities over time. The resource to be allocated refers to some element of sales effort activity such as call time, number of calls, intensity of calls etc. Types of entities can be customers or accounts, services, products, and geographic regions. Because of the need to incorporate dynamic feature in service marketing and most of the models developed so far are static, we explicitly introduce time element in our description of the fundamental problem to keep the model versatile for both dynamic and static application. Any static application of the salesforce hence service effort allocation problem simply represents a special case.

Given this description, a generic formulation of the salesforce allocation model is as follows:

\[
\text{maximize } I(S) = \sum_{t=1}^{T} \sum_{i=1}^{N} p_i(y_{it}(s_1, \ldots, s_N)),
\]

subject to:

\[
\sum_{i=1}^{N} s_i = k_t \quad (t = 1, \ldots, T),
\]

where \(i\) is the entity index, \(t\) is the time index, \(k_t\) is the capacity of the resource in period \(t\), \(s_i\) is the amount of resource allocated to entity \(i\) in period \(t\), and \(p_i(.)\) is the profit (i.e. response) function associated with entity \(i\) in period \(t\). The function \(y_{it}(.)\) is a path-through function introduced strictly for mathematical convenience. It captures the resource allocation history at any given point in time and represents the effect on the response function associated with entity \(i\) caused by the total amount of the resource allocated through period \(t\). In other words, \(y_{it}(.)\) provides for the possibility that \(p_i(.)\) may be a complicated function of the decision variables \(s_1, \ldots, s_N\). For example, perhaps \(y_{it}(.) = \lambda s_1 + (1 - \lambda) (s_1 + \ldots + s_N)\), in which case, \(p_i(.)\) depends on a combination of present as well as cumulative past allocation of the resource. As \((1)\) indicates, the objective is to maximize the sum of payoffs over all customers over the time of the problem horizon. There is one constraint per time period reflecting the fact that there is a limited amount of the resource that may be allocated among the entities each period.

From this generic formulation, we can derive the basic salesforce allocation models introduced in 1971. To demonstrate, suppose \(y(.)\) depends only on the current period’s allocation; i.e. suppose \(y_{it} = y(s_i)\). In this case, there is no link between periods. As a result, \((1)\) reduces to \(T\) separate single period problems, each of which is representative of the CALLPLAN model and its extensions (e.g. Lodish, 1976; Lodish, 1980; Beswick and Cravens, 1977; Zoltners et al., 1979; Lodish et al., 1988). Now suppose \(y_{it}(.)\) depends not only on the current period’s allocation decision, but also on past allocation decisions. In this case, there is a carryover effect and \((1)\) is representative of the DETAILER model and its extensions (e.g. Parasuraman and Day, 1977; Zoltners and Sinha, 1980; Rangaswamy et al., 1990).

In this paper, we extend the notion of carryover by specifying that the response function associated with a given customer depends on the customer’s accumulated level of satisfaction, where satisfaction is discounted as time progresses and sales effort affects customer satisfaction. These basic ingredients also form the underpinnings of DETAILER. However, what distinguishes our model from those of DETAILER, CALLPLAN, and their successors is the computation of the lifetime value of a customer attributed to the time-phased allocation of sales effort when the customer has a preconceived notion of how the effort ought to be allocated over time, which we include because customers typically base their satisfaction on the degree to which their expectations are exceeded. Consequently, we formulate a dynamic model in which the customer response function is updated over time as a result of the customer’s accumulated satisfaction.

### 3. Allocation model formulation

Our modeling effort focuses on strategic insight regarding customer segmentation and selection, aggregate capacity planning, and the tie between service effort allocation, lifetime value, and the service profit chain. This distinguishes the modeling spirit of our research with that of previous research, which, like more generic resource allocation models (e.g. Zipkin, 1980; Luss and Gupta, 1975), focuses on the development of efficient algorithms (both exact and heuristic) for solving \((1)\). Our model also differs from previous approaches in that we include a probabilistic element that, with the exception of Zoltners and Sinha (1980), is notably absent in the salesforce allocation literature. The probabilistic element arises in our model because we base customer response on customer satisfaction. A given customer’s level of satisfaction, in turn, depends on the customer’s preconceived expectation regarding the service experience, which is difficult to predict precisely, especially given that customer preferences often vary at the level of the individual.

Drawing on consumer behavior models, we define customer satisfaction as a function of the level of sales effort allocated to the customer relative to the level of sales effort expected by the customer (Bearden and Teel, 1983; Oliver and Desarbo, 1988; Tse and Wilton, 1988; Thaler, 1985; Parasuraman et al., 1985; Bolton and Drew, 1991). In this paper, we aim not to develop or test consumer behavior models, but rather to focus on decision making using consumer behavior theory as an input. To that end, we introduce a function to represent the customer’s changing expectations over time. And since these expectations depend not only on the decision-making firm’s past performance, but also on the perceived industry standard, which is beyond the control of the decision maker, we include a random component in the formulation of the customer response function.

Specifically, we assume a total salesforce capacity, \(K\), is available to allocate to a single customer over a fixed time span of \(T\) periods. We relax the assumption of a per-period capacity constraint because we are interested first, in identifying an optimal allocation strategy for a given (single) customer type (so that, for example, we can gain insight with respect to how customer types should be targeted/selected), and second, in determining implications to aggregate capacity planning. The periods are defined to correspond to the customer’s fixed purchasing schedule so that the customer makes a purchase at the end of each period. However, the quantity purchased, and therefore the profit realized (i.e. the customer’s response) in a given period, depends on the level of service that the customer receives relative to the customer’s service expectations, which is updated over time based on
each successive service experience. Accordingly, we stipulate the following definitions:

\[ X_t \] \quad \text{random variable indicating level of service expected by the customer in period } t \text{ (expressed in units of sales effort)}

\[ s_t \] \quad \text{decision variable indicating level of service allocated to the customer in period } t \text{ (expressed in units of sales effort)}

\[ Y_t \equiv (s_t - X_t) \] \quad \text{random variable indicating customer satisfaction with respect to service experience in period } t \text{ (} Y_t < 0 \text{ indicates customer dissatisfaction)}

\[ \pi(Y_t) \] \quad \text{random variable indicating profit for period } t, \text{ as a function of customer satisfaction}

We specify that the customer’s service expectation is updated each period as the weighted average of the previous service expectation and the service actually received during the most recent service experience (note that we adopt the convention of counting periods backward so that period 1 is the last period and period } T \text{ the first):}

\[ X_{t-1} = \lambda s_t + (1 - \lambda) X_t, \quad (2) \]

where \( \lambda \) is the weight given to the most recent experience. We treat \( s \) as a known scalar, although an adaptation of the analysis yields similar structural results if a subjective distribution function is used to characterize \( \lambda \). We also specify that \( \pi(y) \) is increasing, concave, and twice differentiable in \( y \). In other words, we specify that profit increases at a decreasing rate as the customer’s satisfaction level exceeds expectations (i.e. as the customer becomes increasingly satisfied); and that profit decreases at an increasing rate as the customer’s satisfaction falls short of expectations (i.e. as the customer becomes increasingly dissatisfied). We mean for this to represent that the incremental penalty associated with dissatisfaction is greater than the incremental reward associated with satisfaction. Such a specification is consistent with the Prospect Theory in behavioral science literature (Kahneman and Tversky, 1979).

For convenience, we define \( \pi'(y) = d\pi(y)/dy \) and \( \pi''(y) = d^2\pi(y)/dy^2 \). To determine the lifetime value of the customer, we adapt (1) and formulate the sales-effort allocation decision scenario as a dynamic program as follows. Let \( G_t(A, X) \) be the the maximum expected discounted profit from period \( t \) to \( 1 \), given that at the beginning of period \( t \), the aggregate capacity available is \( A \) and the level of service expected by the customer is characterized by the random variable \( X \) (having known distribution function). Then:

\[ G_t(A, X) = \max_{s \in A} \left[ E\left[ \pi(s - X) \right] + \alpha G_{t-1}[A - s, \lambda s + (1 - \lambda) X] \right], \quad (3) \]

where \( G_0(\cdot) = 0 \), \( E[\cdot] \) is the expectation operator, and \( \alpha \) is a discounting factor. In (3), \( X \) is a state (random) variable indicating the amount of sales effort expected by the customer as of the beginning of period \( t \) and \( s \) is the decision variable indicating the amount of sales effort allocated to the customer in period \( t \). As a result of the allocation, assuming that \( A \) is the aggregate capacity of sales effort available as of the beginning of period \( t \), the remaining available capacity as of the beginning of period \( t - 1 \) would be \( A - s \); and the customer’s updated expectation for sales effort as of the beginning of period \( t - 1 \) would be \( \lambda s + (1 - \lambda) X \). Thus, (3) is interpreted as follows:

- Given the decision to allocate \( s \) effort to the customer in period \( t \), the immediate contribution to expected profit is \( E[\pi(s - X)] \) and the discounted optimal expected future profit stream is \( \alpha G_{t-1}[A - s, \lambda s + (1 - \lambda) X] \). Accordingly, the lifetime value of the customer, given that \( K \) effort is budgeted for allocation to the customer over the customer’s lifetime of \( T \) periods, is \( G_T(K, X_T) \), where \( X_T \equiv 0, X_T \sim F(x) \), and \( F(x) \) denotes the distribution function assigned to characterize the customer’s service expectations prior to any actual experience.

For convenience, define \( \Pi_t(s, A, X) \) as:

\[ \Pi_t(s, A, X) = E[\pi(s - X)] + \alpha G_{t-1}[A - s, \lambda s + (1 - \lambda) X]. \quad (4) \]

In addition, let \( g_t(A, s) \) be the conditional maximum discounted profit from period \( t \) to \( 1 \), given that at the beginning of period \( t \), the aggregate capacity available is \( A \) and the level of service expected by the customer is specified as \( x \) (i.e. if \( X = x \), then \( G_t(A, X) = g_t(A, x) \)); and let \( s_t^* \) be the optimal amount of sales effort to allocate in period \( t \) (i.e. \( s_t^* \) represents the solution to the maximization associated with stage \( t \) of the dynamic program (3)).

Then, conditioning on \( X = x \):

\[ g_t(A, x) = \pi(s_t^* - x) + \alpha G_{t-1}[A - s_t^*, \lambda s_t^* + (1 - \lambda) x], \quad (5) \]

where \( g_0(A, x) = 0 \). Combining (5) with (4) and (3), after unconditioning:

\[ G_t(A, X) = \Pi_t(s_t^*, A, X) = E[g_t(A, X)]. \quad (6) \]

In addition, we denote the following two functions as boundary values of the first derivative of profit function (\( \Pi \)) with respect to level of service effort \( s \):

\[ h_t(A, X) = \partial_s \Pi_t(s, A, X)|_{s=0}, \quad (8) \]

\[ j_t(A, X) = \partial_s \Pi_t(s, A, X)|_{s=a}. \quad (9) \]

Given these, the optimal solution can be characterized and termed as Theorem 1 in the following:

**Theorem 1.** Given \( A \) and a distribution for the random variable \( X \), the following properties characterize the optimal solution to (3):

- \( j_t(A, X) < h_t(A, X) \). If \( h_t(A, X) \leq 0 \), then \( s_t = 0 \); if \( j_t(A, X) > 0 \) and \( j_t(A, X) < h_t(A, X) \), then \( s_t = s_t(A) \), where \( s_t(A) \) denotes the unique value of \( s \) that satisfies \( h_t(s, A, X) = 0 \).
- \( g_t(A, x) \) is decreasing and concave in \( x \); i.e. \( \partial_x g_t(A, x) < 0 \) and \( \partial_{xx} g_t(A, x) < 0 \).
- \( G_t(A, X) \) is increasing and concave in \( A \); i.e. \( E[\partial_A G_t(A, X)] > 0 \) and \( E[\partial_{AAA} G_t(A, X)] < 0 \).
- \( E[\partial_{AAA} G_t(A, X)] \left[ E[\partial_{XX} G_t(A, X)] - E[\partial_{XXA} G_t(A, X)] \right]^2 \geq 0 \).
- \( G_t(A - s, \lambda s + (1 - \lambda) X) \) is concave in \( s \); i.e. \( E[\partial_s G_t(A - s, \lambda s + (1 - \lambda) X)] < 0 \).

Proof. In the Appendix.

**4. Analytical insight**

Theorem 1 is useful for planning in that it offers a compact and structured expression for the expected lifetime value of a given customer, \( G_T(K, X_T) \), which is expressed as a function of the aggregate salesforce capacity (\( K \)) dedicated to the given
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customer and as a function of the “profile” \((X_T)\) of the given customer (more precisely, the customer’s profile is \(F(x)\), the conditional distribution function of \(X_T\), which represents the decision maker’s subjective probability distribution characterizing the customer’s a priori service level expectation). We next exploit the functional properties of
\[ G_T(K, X_T) \]

to determine first, how much capacity should be committed to a given customer, and second, how to choose a customer in the first place.

Aggregate capacity planning

From Theorem 1, the expected lifetime value of a given customer is increasing and concave as a function of \(K\), the aggregate \(T\)-period capacity dedicated to the given customer. In addition, given \(K\), Theorem 1 produces an optimal allocation schedule over the \(T\)-periods. Let \(s^*(K)\) denote the vector of optimal allocation decisions over \(T\) periods implied by Theorem 1 when \(K\) capacity is dedicated. Suppose \(C(K) = C[s^*(K)]\) is a cost incurred to establish/dedicate a salesforce with \(K\) total capacity to service a given customer over \(T\) periods, given that an optimal allocation schedule is implemented for that capacity. If \(C(K)\) is convex in \(K\), then \(g_T(K, X_T) - C(K)\), which represents the net expected profit associated with the \(T\)-period relationship with the customer, is concave. Therefore, in this case, \(K^*\), the optimal capacity to commit to the given customer, can be determined as the unique value of \(K\) that satisfies
\[ E[\varphi(K, X_T)] = dC(K)/dK. \]

Intuitively, \(K^*\) balances the marginal expected discounted revenue generated through sales contact over the lifetime of a given customer with the marginal discounted cost of providing that contact.

Customer selection

A given customer is defined by \(X_T\), the random variable indicating the decision maker’s characterization of the customer’s a priori expectations for level of service (more precisely, the customer is defined by \(F(x)\), the distribution function used to characterize \(X_T\)). From Theorem 1, \(g_T(K, x)\), the conditional lifetime value of a given customer, given that \(X_T = x\), is decreasing and concave in \(x\). This property indicates that, under appropriate circumstances, customers can be ranked from most favorable to least favorable [1].

The definition of increasing convex ordering applied with Theorem 1 means that if given the choice between two random variables \((X_T\) and \(X'_T)\), each of which represents a different customer profile [2], and if one random variable is smaller than the other in the increasing convex ordering, then the smaller of the two random variables is preferable because it yields a higher expected lifetime value of the customer. The corresponding increase in the expected lifetime value of a customer can be interpreted as a form of value of information. Next, we discuss two immediate implications of this preference ordering of distributions.

First, consider a single customer whose a priori expectation for level of service is characterized by a random variable \(X_T\) having the distribution \(F_{X_T}(x)\). And, let \(c(X_T)\) denote the investment required to obtain information necessary to refine the distribution function, perhaps through surveys or other forms of market research, such that the refined distribution is more favorable in that it satisfies the test for increasing convex ordering. Then, the viability of the investment is determined by comparing the cost of refinement with the benefit of an increased expected lifetime value of the customer. For a general convex cost function \(c(\cdot)\), the optimal level of refinement equates the expected marginal benefit with the marginal cost of incrementally “better” distributions. Such a property can help managers calculating the optimal marketing research and promotional budgets to refine the distribution of customer’s expectation on service level. Hence, help cultivate more satisfied customers and higher customer lifetime values for the marketer.

Second, consider a pool of potential customers from which one customer with whom to build a relationship is to be chosen. Let potential customer \(i\) be identified uniquely by \(X_T\). Then, if an increasing convex ordering of the customers is possible, then a preference ranking among the customers can be determined directly. This property can help marketer to allocate their service efforts in the preference order; hence, help maximize the profits and the effect of long-term service efforts.

This form of customer ranking also has direct applicability to choosing between a new customer and an existing customer.

5. Managerial implications and conclusion

An effective and efficient servicing process is essential to a firm’s success and even survival in today’s globally competitive world (Rottenberger-Murtha, 1993). In response, many firms are reevaluating their market presence, implementing steps to increase their focus on markets that allow them to leverage their core competencies, and developing processes to serve these markets more productively. In many cases, provider firms have either dissolved, restructured, or outsourced to third party representatives or distributors the bulk of their sales functions and have maintained servicing of only its most important customer accounts (i.e. those accounts in which relationships can be built to extract long-term customer value). The prevalence of such relationship accounts (e.g. national accounts, international accounts, key accounts, large accounts, and strategic accounts) is such that virtually all major industrial organizations include them in some form (Boles et al., 1994; Gummesson, 2004).

While this is a descriptive study investigating different behavioral models, the salesforce hence service effort allocation model presented in this paper is particularly useful for establishing and managing such accounts in that it provides insight into the strategic selection of and aggregate resource planning for a particular customer with whom a long-term relationship can be established. The model builds from the initial premise that customer demand can be affected by activities endogenous to the firm; that is, customer demand is a control variable. Specifically, we assume that customers aim to maximize the value that they receive from a purchase, where value is defined as the sum of the intrinsic product quality in terms of output or results and the extrinsic quality of the purchasing process in terms of service encounter experience, divided by price. Given this customer-value function, the firm has three controls through which it can increase customer value, and thereby increase demand: price, intrinsic product quality, and extrinsic quality of the service encounter.

Incorporating the demand function into organizational decision making through the explicit modeling of the customer-value function is a natural application for scientific management. Indeed, analytical models abound for affecting customer demand through price (re: microeconomic pricing models) or through intrinsic product quality (re: product design models). However, we are not aware of any normative approaches incorporating the quality of the service encounter
explicitly as a decision variable. This is one reason for appeal of the focus of this paper. A second, more important, appeal stems from the flexibility that service encounter-quality provides to the decision maker. Since time and effort is infinitely divisible and adjustments can be made practically instantaneously, service encounter-quality can be tailored to the level of the individual customer at relatively little cost. Neither price nor intrinsic product quality, as control variables, provide this degree of flexibility to the decision maker. A strict regulatory environment limits the degree to which prices may be tailored to individual customers; and technological or cost restrictions limit the degree to which instantaneous tailoring of intrinsic product quality can be achieved. Thus, service-encounter quality offers the most leverage to the firm in terms of extracting the maximum amount of utility from its customer base.

Given that customer demand is a function of the quality of the service encounter, we demonstrate that the lifetime value of a customer is a key driver not only in allocating the service effort (hence the salesforce) resources available to develop and manage a relationship with a customer, but also in determining whether or not a long-term relationship even should be developed with a specific customer. Further, we identify a parallel application for developing and managing relationships with internal customers (i.e. employees). Thus, through the context of the service profit chain, and in the spirit of relationship efforts as an important strategic issue.

The analysis and insights developed in this paper focus exclusively on how the notion of lifetime value applies to developing or managing relationships with external customers. The model can also be extended to developing and managing relationships with internal customers (i.e. employees). The key premise to such an extension is that more satisfied employees translates into more productive employees (correspondingly, the amount of aggregate resource dedicated to satisfying the employee over a given planning horizon \( K \)). Moreover, the results of the model can be used to determine \( K \), as well as how to select an employee in the first place.

There are a few limitations to this paper. As a descriptive study investigating different behavioral models, this paper focuses on providing a clear theoretical contribution and a set of theoretical implications for service managers to incorporate in their decision-making thinking process. The theoretical contribution this paper adds to the literature lies in exploring the link between service quality and profitability (service profit chain) by managing sales efforts. It expands service profit chain by adding the link between salesforce management and service quality which leads to profitability. It demonstrates how existing salesforce management, in particular optimal sales effort allocation, can be useful for service marketers to increase service quality level, in turn, increase the long-term profitability. This is particularly valuable as Key Account Management has become more and more important because of the increasing needs to develop and retain relationships with large scale or globally operated businesses (Mattgard and Astrom, 2004). Unlike those 1-2-3 step action guidelines, the implications discussed are analytical and meant to help service managers shaping their thought process in their decision making. Finally, future research can be directed toward empirically testing the model proposed in this study to provide service managers calibrated parameters for their decision making in measurable manners.

Notes

1 To demonstrate, consider the following stochastic ordering definition from Ross (1983): a random variable \( X_T \) is larger than \( X_T' \) in the increasing convex ordering (denoted \( X_T \geqso X_T' \)) if \( \int_{\mathbb{R}} [1 - F_{X_T}(\theta)] \, d\theta \geq \int_{\mathbb{R}} [1 - F_{X_T'}(\theta)] \, d\theta \) for all \( x \) (where \( F_X(x) \) denotes the distribution function for \( X \)); moreover, \( X_T \geqso X_T' \iff E[r(X_T)] \leq E[r(X_T')] \) for all decreasing concave functions \( r(\cdot) \). This type of stochastic ordering is a form of variability comparison. The reason for this is twofold (Song, 1994):

   (1) if \( X_T \geqso X_T' \) and \( E[X_T] = E[X_T'] \), then \( \text{Var}(X_T) \geq \text{Var}(X_T') \); and (2) if \( X_T \geqso X_T' \), then \( X_T \) is noisier than \( X_T' \), which means that there exists a random variable \( e \), with \( E[e|X_T] \geq 0 \) almost surely, such that \( X_T = X_T + e \) is equal in distribution to \( X_T + e \). Many pairs of standard distributions satisfy the condition for increasing convex ordering; see, for example, Ross (1983) and Song (1994).

2 As defined by each random variable’s distribution function.
References


Appendix. Proof of Theorem 1

Given a distribution function for \( X \), say \( \Phi(x) \), let

\[
\frac{\partial G_i(A, X)}{\partial x} = \Phi^*(\frac{x}{\lambda}) - \Phi(\frac{x}{\lambda}) = \int_0^x \Phi^*(\frac{u}{\lambda}) \, du - \int_0^x \Phi(u) \, du = \Phi^*(\frac{x}{\lambda}) - \Phi(u).
\]

and

\[
\frac{\partial^2 G_i(A, X)}{\partial x^2} = \Phi^*(\frac{x}{\lambda}) - 2\Phi(u) + \Phi^*(\frac{x}{\lambda}) = \Phi^*(\frac{x}{\lambda}) - \Phi^*(\frac{x}{\lambda}) - 2\Phi(u) + \Phi^*(\frac{x}{\lambda}) = -2\Phi(u).
\]

Then, from (4):

\[
\frac{\partial \Pi_i(s, A, X)}{\partial s} = E[\pi^*(s - X)]
\]

\[
- \alpha \left( \frac{\partial G_{i-1}(u, V)}{\partial u} - \lambda \frac{\partial G_{i-1}(u, V)}{\partial V} \right),
\]

(A1)

where \( u = A - s \) and \( V = \lambda s + (1 - \lambda) X \). Given the definition of \( s_i^* \), if \( s_i^* \) is an interior point, then it satisfies \( \frac{\partial \Pi_i(s, A, X)}{\partial s} = 0 \). Thus, intuitively, \( s_i^* \) is determined by balancing the expected marginal gain in current profit with the cumulative expected marginal loss in future profit resulting from an increased allocation of effort to the current period. The opportunity cost of future profit arises from two factors: a higher allocation of effort to the current period (i) reduces the amount of aggregate effort available for allocation to future periods and (ii) increases the service expectation level of the customer, thereby increasing the amount of effort required to sustain the same level of satisfaction. If \( s_i^* \) does not satisfy \( \alpha \Pi_i(s, A, X) / \partial s = 0 \), then \( s_i^* \) is a boundary point.

From (A1), for \( t = 1 \),

\[
\frac{\partial \Pi_i(s, A, X)}{\partial s} = E[\pi^*(s - X)] > 0,
\]

where the inequality follows because \( \pi^*(s - X) > 0 \) for any given \( X = x \), by assumption. Consequently, \( s_t = A \), a boundary; and thus, from (5),

\[
g_t(A, x) = \pi(A - x), \]

which implies the following:

\[
\frac{\partial g_t(A, x)}{\partial x} = -\pi(A - x) < 0;
\]

\[
\frac{\partial^2 g_t(A, x)}{\partial x^2} = \pi^*(A - x) < 0;
\]

\[
E[g_t(A, X)/\partial A] = E[\pi^*(A - X)] > 0,
\]

and

\[
E[\pi^2(A, X)/\partial^2 A] = E[\pi^*(A - X)] < 0.
\]

Thus, \( g_t(A, x) \) is increasing and concave in \( s_t \) and \( G_t(A, X) \) is increasing and concave in \( A \). Moreover,\n
\[
E[\pi^2 g_t(A, X)/\partial^2 A] = E[\pi^*(A - X)] < 0.
\]

Thus, \( g_t(A, x) \) is decreasing and concave in \( s_t \) and \( G_t(A, X) \) is increasing and concave in \( A \). Moreover,\n
\[
E[\pi g_t(A, X)/\partial A] = E[\pi^*(A - X)] > 0.
\]

Having now established basic properties for the case when \( t = 1 \), we identify similar properties for an arbitrary \( t \). We discuss managerial implications in the next section. In the spirit of conserving space, we adopt the following notation in establishing the proofs (which appear in the Appendix): given a function of two arguments, \( u \) and \( v \), we let \( g_u(\cdot) \) and \( g_v(\cdot) \) represent the first and second partial derivatives, respectively, with respect to \( u \) or \( v \), and we let \( g_{uv}(\cdot) \) represent the cross partial. In addition, we define the two functions shown earlier in (8) and (9).

Assume (a)-(c) in Theorem 1 are true for \( t = 1, \ldots, i - 1 \) and let \( t = i \).

(1) Property (a).

From (4),

\[
\Pi_i(s, A, X) = E[\pi^*(s - X)] + \alpha G_{i-1}(u, V),
\]

where \( u = A - s_i \) and \( V = \lambda s_i + (1 - \lambda) X \). From induction hypothesis (c), \( G_{i-1}(u, V) \) is concave in \( s \). And, by differentiation, \( E[\pi^*(s - X)] \) is concave in \( s \). Thus, \( \Pi_i(s, A, X) \) is concave in \( s \). Therefore, \( \Pi_i(s, A, X) \) is decreasing in \( s \), which implies, from (8) and (9), that \( j_i(A, X) < h_i(A, X) \).

Correspondingly, given \( A \) and a distribution for the random variable \( X \) if \( h_i(A, X) < 0 \), then \( \Pi_i(s, A, X) \) is decreasing in \( s \) for all \( s \), indicating that \( s_i^* = 0 \); if \( j_i(A, X) > 0 \), then \( \Pi_i(s, A, X) \) is decreasing in \( s \) for all \( s \) indicating that \( s_i^* = A \); and if \( j_i(A, X) > 0 < h_i(A, X) \), then \( \Pi_i(s, A, X) \) is zero exactly once, at \( s_i^* \), indicating that \( s_i^* = h_i(A, X) \).

(2) Properties (b), (c), and (d). Given (5) and Property (a), \( g_t(A, x) \) can be expressed as follows:

\[
g_t(A, x) = \begin{cases} 
\pi_i(-x) + \alpha g_{i-1}(A - (-1 - \lambda) x) & \text{for } s_i^* = 0 \\
\pi_i(A - x) + \alpha g_{i-1}(A - (1 - \lambda) x) & \text{for } s_i^* = s_i(A) \\
\end{cases}
\]

\[
g_t(A, x) = \begin{cases} 
\pi_i(A - x) + \alpha g_{i-1}(A - (1 - \lambda) x) & \text{for } s_i^* = s_i(A) \\
\end{cases}
\]

Given a distribution for \( X \), define \( A_0 \) as any point that is such that \( h_i(A_0, X) = 0 \). From property (a), if \( A = A_0 \), then \( s_i^* = 0 \).

Now, consider the value of \( A_0 \) as \( A \) approaches a point \( A_i \) from a point that is such that \( j_i(A, X) < 0 < h_i(A, X) \), in which case, from property (a), \( s_i^* = s_i(A) \). By definition, \( s_i(A, X) \) is determined by

\[
\Pi_i(s, A, X) \bigg|_{s=s_i(A)} \rightarrow \Pi_i(s, A, X) \bigg|_{s=s_i(A)} = 0 = h_i(A, X)
\]

\[
\Rightarrow \Pi_i(s, A, X) \bigg|_{s=s_i(A)} = 0
\]
Consequently, $s_i(A) \rightarrow 0$ as $A \rightarrow A_b$, which implies that $s_i$ is continuous over such boundaries.

Similarly, define $A_j$ as any point that is such that $j_1(A_j, X) = 0$. From property (a), if $A = A_j$, then $s_i = 0$. Now, consider the value of $s_i$ as $A$ approaches a point $A_j$ from a point that is such that $j_1(A_j, X) < 0 < h_i(A, X)$, in which case, from property (a), $s_i = A_j$. By definition, $\partial_i \Pi_i(s, A, X)|_{s=A_j} = 0$. Thus, as $A \rightarrow A_j$:

$\partial_i \Pi_i(s, A, X)|_{s=A_j} - \partial_i \Pi_i(s, A_j, X)|_{s=A_j} = 0 = j_1(A_j, X)$

Consequently, $s_i(A) \rightarrow A_j$ as $A \rightarrow A_j$, which implies that $s_i$ is continuous over such boundaries as well. Correspondingly, $s_i$ is continuous everywhere and therefore, $g_i(A, x)$ is continuous everywhere. Using a similar approach, it also can be shown that $g_i(A, x)$ is differentiable everywhere.

Given that $g_i(A, x)$ is continuous and differentiable, we can complete the proof of this property by demonstrating the desired properties separately for each of the three possible forms that $g_i(A, x)$ may take.

**Case I ($s_i = 0$):**

Suppose $g_i(A, x) = \pi(\gamma(x) + \alpha g_{i-1}(A_i (1 - \gamma) x)$ and let $\gamma = 0$. Then, by induction hypotheses (b)-(d):

$E[\partial A_{gi}(A, V)] = 0$; 

$E[\partial \sigma_{i-1}(A, y)] < 0$; 

$E[\partial \sigma_{gi, l}(A, V)] < 0$; 

$E[\partial \sigma_{i} g_{i-1}(A, V)] > 0$; 

$E[\partial \sigma_{i} g_{i-1}(A, V)] > 0$.

Thus:

$\frac{\partial g_i}{\partial y} = \frac{\partial g_i}{\partial A_{gi}} = \frac{\partial g_i}{\partial \sigma_{i-1}} = \frac{\partial g_i}{\partial \sigma_{gi, l}} = \frac{\partial g_i}{\partial \sigma_{i}} > 0$.

$E[\partial A_{gi}(A, V)] = 0$; 

$E[\partial \sigma_{i-1}(A, y)] < 0$; 

$E[\partial \sigma_{gi, l}(A, V)] < 0$; 

$E[\partial \sigma_{i} g_{i-1}(A, V)] > 0$.

$E[\partial \sigma_{i} g_{i-1}(A, V)] > 0$.

Hence, $g_i(A, x)$ is decreasing and concave in $x_i$ and $G_i(A, X)$ is increasing and concave in $A$. Moreover:

$\begin{align*}
\partial g_i(A, x) &= -\pi'(s_i(A) - x) + \alpha(1-\lambda) \partial g_{i-1}(u, v) < 0; \\
\partial g_{ii}(A, x) &= \pi'(s_i(A) - x) + \alpha(1-\lambda)^2 \partial g_{i-1}(u, v) < 0;
\end{align*}$

$E[\partial g_i(A, X)] = \alpha E[\partial g_{i-1}(u, V)] > 0$;

$E[\partial A_{gi}(A, X)] = \alpha E[\partial u_{i}(u, V)] - \alpha E[\partial u_{i} g_{i-1}(u, V)] E[\partial s_i(A)] = + \frac{\alpha E[\pi'(s_i(A) - X)] E[\partial u_{i} g_{i-1}(u, V)]}{\partial s_i \Pi_i(s, A, X)|_{s=s_i(A)}}$

$\begin{align*}
\partial_{ss} \Pi_i(s, A, X)|_{s=s_i(A)} &= \alpha^2 \lambda^2 \left( E[\partial u_{i} g_{i-1}(u, V)] E[\partial v_{i} g_{i-1}(u, V)] - \left( E[\partial u_{i} g_{i-1}(u, V)] \right)^2 \right) < 0;
\end{align*}$

Figure A1
Thus, by applying induction hypotheses (b)-(d) we arrive at the equation in Figure A1 and, after some algebra (dropping functional arguments for compactness) we obtain the equation shown in Figure A2. Property (e). From (6),

\[
\frac{\delta_s G_i(u, V)}{E[\delta_{V'V} g_i(u, V)]} = \frac{E[\delta_{uV} g_i(u, V)] E[\delta_{V'V} g_i(u, V)] - 2\lambda E[\delta_{uV} g_i(u, V)] E[\delta_{V'V} g_i(u, V)] + \lambda^2 E[\delta_{V'V} g_i(u, V)]^2}{E[\delta_{V'V} g_i(u, V)]} < 0
\]

and

\[
\delta_s \prod_{s(A)} E[\pi^0(s(A) - X)] + \alpha E[\delta_{uvA} - 1(u, V)] - 2\lambda \delta_{uvG_i - 1}(u, V) + \lambda^2 \delta_{V'VG_i - 1}(u, V)
\]

Thus, by applying induction hypotheses (b)-(d) we arrive at the equation in Figure A1 and, after some algebra (dropping functional arguments for compactness) we obtain the equation shown in Figure A2. Property (e). From (6),

\[
G_i[A - s, \lambda s + (1 - \lambda)X] = E[g_i[A - s, \lambda s + (1 - \lambda)X]].
\]

Let \(u = A - s\) and \(V = \lambda s + (1 - \lambda)X\). Then, by applying the chain rule twice:

\[
\delta_s G_i(u, V) = E[\delta_{uV} g_i(u, V)] - 2\lambda E[\delta_{uV} g_i(u, V)] E[\delta_{V'V} g_i(u, V)] + \lambda^2 E[\delta_{V'V} g_i(u, V)]^2
\]

Thus the implied the equation shown in Figure A3. But, property (d) implies that \(E[\delta_{uV} g_i(u, V)] E[\delta_{V'V} g_i(u, V)] \geq E[\delta_{uV} g_i(u, V)]^2\); and property (b) implies that \(\delta_{V'V} g_i(u, V) < 0\), which in turn implies that \(E[\delta_{V'V} g_i(u, V)] < 0\). Thus we obtain the equation shown in Figure A4.

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Executive summary and implications for managers

This summary has been provided to allow managers and executives a rapid appreciation of the content of the article. Those with a particular interest in the topic covered may then read the article in toto to take advantage of the more comprehensive description of the research undertaken and its results to get the full benefit of the material present.

How many times do companies tell people “We value your custom” or “Your custom really matters” or claim to adhere to the adage about the customer always being right?

Commercial organizations certainly must, and do, recognise that the customer matters – without the customer, especially a satisfied one who comes back with repeat business, there would be no business activity, no profit and no future for the company. That’s why the people who manage sales forces worry so much about how best to satisfy the needs of diverse customer groups, especially managers in companies which provide goods or services for which there are many competitor suppliers.

Their concern stems from a determination to understand such variables as the customer’s needs and patterns of buying. Valuable as customers are, and accepted that every customer matters, sales forces have limited resources and it has to be accepted that some customers are more valuable than others, and consequently some matter more than others. Treating them differently might seem unfair, but it certainly makes sense.

As Ben Shaw-Ching Liu et al. note: “Given the differences between customers, it is useful to categorize customers on the basis of their differences before allocating sales effort to them. Then, given a fixed sales capacity, we could determine the potential lifetime value of a given customer type associated with the available capacity. This essential calculation provides an important source of information to managers charged with allocating service effort through sales capacity.”

How much capacity should be committed to a given customer type? And which customer type should be given priority in terms of committing capacity?

The authors’ model of resource allocation differs from others by its computation of the lifetime value of a customer attributed to the time-phased allocation of sales effort when the customer has a preconceived notion of how the effort ought to be allocated over time. This aspect is included because customers typically base their satisfaction on the degree to which their expectations are exceeded. Consequently, this is a model in which the customer response function is updated over time as a result of the customer’s accumulated satisfaction.

Customer value and firm profit are inextricably linked by an update of customers’ experiences and perceptions. The idea is that customer relationship management designed to provide increased value to the customer ultimately yields a lifetime value to the service provider.

Ben Shaw-Ching Liu et al. say: “The two broad dimensions of service quality are such that one dimension captures ‘what’ the customer purchases in terms of output or results, and the second dimension captures ‘how’ the customer perceives the process through which the purchase occurs.”

Customers differ in terms of how they update over time their initial expectations in the light of the service level they actually receive – they have their impression of the most recent transaction and another one of the cumulative effect of that and previous encounters. But, although the analysis and insights focus on how the notion of a lifetime value applies to developing or managing relationships with external customers, the model can be extended to developing and managing relationships with employees (the “internal” customers). In other words the more satisfied employees the more productive employees (and the reverse).

Corresponding to the link between customer satisfaction and firm profit, the link between employee satisfaction and firm productivity hinges on value. Value can be defined as the ratio of the overall benefit received to the overall cost incurred. From the customer’s perspective, this translates into service quality divided by service price and, from the employee’s viewpoint, its job quality divided by job price.

An employee’s “price” function can be thought of as the time and energy devoted to accomplish specifications of the job. An employee’s corresponding “quality” function, analogous to a customer’s quality function, is the aggregation of a preference set comprising multiple dimensions which include pay, benefits and training.

In many cases, provider firms have either dissolved, restructured, or outsourced to third party representatives or distributors the bulk of their sales functions and have maintained servicing of only their most important customer accounts (i.e. those in which relationships can be built to extract long-term customer value). The service effort allocation model presented is particularly useful for establishing and managing such accounts in that it provides insight into the strategic selection of and aggregate resource planning for a particular customer with whom a long-term relationship can be established.

Another appeal of the model stems the flexibility the service encounter-quality provides to the decision maker. Since time and effort is infinitely divisible and adjustments can be made practically instantaneously, service encounter-quality can be tailored to the level of the individual customer at relatively little cost.

Neither price, nor intrinsic product quality, as control variables, provide this degree of flexibility to the decision maker.

(A précis of the article “A service effort allocation model for assessing customer lifetime value in service marketing”. Supplied by Marketing Consultants for Emerald.)