Manufacturing & Service Operations Management

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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Delivering high quality service during the service encounter is central to competitive advantage in service organizations. However, achieving such high quality while controlling for costs is a major challenge for service managers. The purpose of this paper is to present an approach for addressing this challenge. The approach entails developing a model linking service process operational variables to service quality metrics to provide guidelines for service resource allocation. The approach enables the service operations manager to take specific actions toward service quality improvement, in light of the costs involved. A novel feature of the approach is the development of robust optimization models, which provide optimal operational guidelines while accounting for uncertainty in the model's parameters. We demonstrate the applicability of the approach in a large health care facility.
(*Service quality; Robust optimization*)

1. Introduction

Competition in services in the 1990s, like competition in manufacturing in the 1980s, often boils down to quality. While many service organizations have always been known for quality, *exceptional* quality has usually been associated with an upscale niche, not considered to be a qualifying condition to compete in less exclusive markets. At the dawn of the new millennium, however, this picture is rapidly changing. The competitive emphasis on "delighting the customer," the widespread awareness of the Baldrige award criteria, the increasing popularity of ISO 9000 standards, etc., have led to more than 93% of all large U.S. corporations having initiated some form of service quality (SQ) improvement program (Rust et al. 1994).

Service quality, of course, is not sought for its own sake; rather, its specific purpose is to raise customer satisfaction with the service received. Customer satisfaction, in turn, has been shown to correlate positively with global performance measures such as repurchase intentions (Bolton and Drew 1991a,b; Boulding et al. 1993), customer retention (Reicheld and Sasser 1990), market share (Kordupleski et al. 1993), financial return (Fornell 1992, Anderson et al. 1994, Rust et al. 1994), and various measures of financial performance (Roth and Jackson 1995).

The quest for improving service quality must be moderated by the realities of personnel, facilities, technology, and other operating costs. As a result, trade-offs must often be made. According to Rust et al. (1994, p. 6), "spending on quality is like any other resource allocation decision; it is expected to produce returns that are greater than the costs." Yet, with few exceptions (see, for example, Rust et al. 1994) there is a dearth of literature on analytical methodologies to help service managers make such trade-offs. There is also a dearth of studies that provide specific guidelines for explicitly linking customer feedback to operational decision making regarding such issues as job and process design, layout design, employee scheduling, training,

1523-4614/00/0203/0264$05.00
1526-5498 electronic ISSN

and facility appearance. (See Roth and Van der Velde 1991 for a discussion on the importance of linking operations and marketing variables to improve performance.) Furthermore, with almost no exceptions (Rust et al. 1994), most of the service quality improvement efforts in the literature focus on the organizational level. They do not consider the important real-life issue of changing customer perceptions that arise as the customer moves through different stages of service within the service organization. Although little is known of *how* perceptions evolve during the service delivery process (Mattsson 1994), such microlevel changes need to be taken into consideration when operational decisions are made.

In this paper, we present a service quality improvement approach that can be adopted to multistage service processes. The specific goal of the paper is to provide the service manager with clear guidelines on how to improve SQ while controlling for costs in an environment where customers' perceptions change as service delivery unfolds. A novel feature of the approach is the use of optimization as a tool for SQ improvement. Although optimization techniques have been widely applied in manufacturing, their adoption to "softer" areas, such as service quality improvement, has been almost nonexistent. A second novel feature is the specific optimization technique employed—that is, robust optimization. This state-of-the-art technique (Mulvey et al. 1995) can take into consideration uncertainty resulting from measurement errors and/or noisy information. This is important because the existence of noisy data is more often the rule than the exception in real-life service systems. The approach is demonstrated through an application in a large health care facility.

The rest of the paper is structured as follows: Section 2 presents some brief background on service quality and on robust optimization. Section 3 describes an approach based on robust optimization that can be used to improve SQ. Section 4 demonstrates the approach as applied in a health care setting, specifically an outpatient clinic. Issues of research design, data collection and analysis, and managerial implications are also discussed. Section 5 presents limitations and future research directions. Concluding remarks follow in §6.

2. Background

2.1. Service Quality

Since the late 1970s, when the distinctive characteristics of services vis-á-vis goods became well recognized (Chase 1978, Sasser et al. 1978), a number of different definitions of quality in services has been introduced (see Lehtinen and Lehtinen 1985, Gröönroos 1983). Today, the definition of service quality, and its relationship to other constructs of interest, are still being actively researched (Oliver 1993, Zahoric and Rust 1993). One of the most popular definitions of service quality is provided by Parasuraman et al. (1985), who define SQ as a form of attitude, related but not equivalent to the construct of customer satisfaction, which results from the customer's perception of service in relation to his or her expectations of service. Based on this definition, Parasuraman et al. (1988) present SERVQUAL, a 22–item survey instrument that compares customer assessments of their service expectations with their actual experience, to derive a gap score. While the methodology and generality of the SERVQUAL gap model have been questioned (Babakus and Boller 1992, Babakus and Manegold 1992), its sharpest critics (Cronin and Taylor 1992, 1994) present results that support its use when modified to have customers score the service on perceived performance only. This modification was used in the present research study.

The realization that attaining high service quality is a cross-disciplinary issue has led to a growing number of studies in several business fields. The human resource management literature, for example, provides a number of studies in which personnel practices have been investigated with respect to their relationship to customers' perceived quality. Schneider and Bowen (1984, 1985, 1993) report strong positive correlations between external and internal customer perceptions of service quality. Other studies (Dennison 1990, Mitchell et al. 1990) examine the effect of employee involvement practices on broad company performance indicators, such as return on sales and return on investment. SQ delivery is also the focus of a growing number of studies within the operations and marketing fields. Of particular importance are those that develop methodologies to link marketing and operational variables to improve the performance of the service delivery system (Bolton and Drew 1991b, Collier 1991). In one of the first studies of its kind, Collier (1991) demonstrates how structural equation modeling can be used to link operations and marketing variables. More specifically, he demonstrates how the development of "service quality maps" based on marketing/operations linkages can aid management decision making. In another study, Behara and Chase (1993) present Service Quality Deployment, a technique based on Quality Function Deployment (Hauser and Clausing 1988), which employs SERVQUAL dimensions to relate customer attributes to service provider behaviors.

Most studies that link operations and marketing variables to improve performance focus on the organizational level. Collier (1991), for example, uses organizational level data to build "service process maps"; however, customers' changing perceptions within the service organization are not taken into consideration. Rust et al. (1994) examine the impact of customer satisfaction on customer retention and market share by modeling the relationship between process satisfaction and profitability via a chain of effects, which they convert to general equations. They also stress the importance of examining how customer perceptions change at lower levels of analysis. With the exception of these works, no studies providing methodologies to link operations/marketing variables at the front-line level were found.

The approach presented in this paper is similar to the one presented by Rust et al. (1994) in that it focuses on levels of analysis lower than that of the organization to improve SQ. However, it differs from this work and other efforts in the following important respects. First, it considers how customer perceptions change as they go through the service system, and employs an optimization methodology to improve SQ decision making. Second, the optimization model employed explicitly accounts for uncertainty as a result of noisy or erroneous data—a typical phenomenon in service systems. Finally, it employs the "three Ts" breakdown of encounter quality dimensions—task, treatment, and tangible—a simple trichotomy with useful properties for evaluating service operations (Chase and Stewart 1994).

2.2. Robust Optimization

Management science has provided an abundance of mathematical programming models for manufacturing problems. Although such models are developed using real data, they usually are treated as deterministic, with formulations based on "best guesses" of uncertain parameters or "worst-case" scenarios. Such approaches, however, are not adequate when incomplete or inaccurate information is the only information available to the modeler. This is the case, for example, when survey data are available. Here, incomplete data and/or random sampling error will be observed no matter how technically proper are the probability sampling techniques used.

To deal with data uncertainty, sensitivity analysis is typically utilized to assess the impact of data perturbations on the solution of the mathematical programming model. Sensitivity analysis is, however, a reactive post-optimality procedure, which only examines the impact of data changes on the model's recommendations. Recently, Mulvey et al. (1995) developed a proactive approach called *robust optimization* (RO), designed to yield solutions that are less sensitive to data uncertainty. The basic robust optimization model as presented by Mulvey et al. (1995) is shown in Appendix A. The approach employs a scenario-based description of the problem data to generate a series of solutions that are progressively less sensitive to different data realizations. The advantages of RO have been discussed elsewhere (Mulvey et al. 1995, Bai et al. 1997), but the most important of these remains that RO can provide recommendations that are relatively immune to expected uncertainty in the parameters of the problem. In the next section we present a general approach, which utilizes RO, to help improve service quality decisions in the presence of noisy data.

3. An Approach to Improve Service Quality

As asserted at the outset of this paper, service delivery often involves the customer in a number of processing stages. As customers perceptions change from stage to stage (Mattsson 1998), it is important to examine such changes and take them into consideration when making operational decisions. The service manager has direct control only over a set of operational variables, not all of which necessarily influence SQ perceptions. A major challenge to the manager, therefore, is to identify those operational variables that can influence SQ perceptions and over which he/she has direct control, and then to manage these in light of financial and/or other constraints. This forms the basis of the three–step SQ improvement approach described below.

Step 1: For each service stage, assess and match SQ customers' perceptions with relevant operational variables.

For each service stage, two types of information need to be collected: information regarding SQ perceptions and information regarding operational variables that might affect these. A blueprint (Shostack 1987) can prove useful in identifying relevant stages of the service delivery system. SQ perceptions can be measured using an existing or modified SQ measurement instrument to better reflect the microlevel of analysis. Such measures must be matched with information on operational variables at each processing stage. Management's input regarding the choice of such variables is critical. Chase and Stewart (1994) describe a theoretical conceptual framework known as the 3Ts that could be used as a starting point to identify such relevant operational variables. The 3Ts framework classifies operational variables into three major dimensions, namely the dimensions of treatment, task, and tangible. The *treatment* dimension includes those operational variables that reflect the behavioral aspects of service delivery. The *task* dimension includes the structural elements of the provided service that influence quality perceptions. Finally, the *tangible* dimension includes sensory factors such as cleanliness, facility attractiveness, and staff appearance.

Step 2: Establish relationships between process operational variables and SQ perceptions for each processing stage.

Establishing relationships between operational variables and perceptions of the different dimensions of SQ can identify improvement opportunities. This is not a trivial task as these relationships can be nonlinear and complex. Armstrong (1991) experimented with different parametric and non-parametric estimation techniques to conclude that linear models can provide adequate fits. Although linear models represent a good starting point, further investigation into other methods to model the relationships between SQ perceptions and service process operational variables is necessary.

Step 3: Incorporate budget, physical, and other resource limitations to identify desirable target levels of process operational variables.

The established relationships of Step 2 between SQ perceptions and operational variables at each stage can provide important insights on desirable changes. However, not only the impact of these changes on the different dimensions of SQ may vary, but such changes may also be constrained by budget and/or other physical limitations. It could be of great benefit to the service manager if an "optimal" operating characteristic mix is identified that maximizes SQ perceptions, given specific service delivery system limitations. Consider, for example, a single service stage, where the following general optimization problem arises:

(M1)

$$\text{maximize} \quad f(d^T y) \tag{1}$$

$$\text{subject to} \quad Ax = y \tag{2}$$

$$Bx = c \tag{3}$$

where,

y: a vector of service quality dimensions $y_1, y_2, \ldots, y_M$, $y \in \Re^M$

x: a vector of operational variables $x_1, x_2, \ldots, x_K$, $x \in \Re^K$

d: a vector of importance weights of SQ dimensions y_j, for each SQ dimension $j = 1, 2, \ldots, M$

A: matrix of model parameters relating operational variables to SQ

B: matrix of model parameters relating operational variables to service system characteristics

c: vector of model parameters reflecting different stage characteristics

In **(M1)** the objective function (1) maximizes perceptions of SQ. This is a function of the different SQ dimensions evident at each service stage. The set of equations (2) relates process characteristics to SQ dimensions. Additional constraints can be added to reflect available resources, such as budget, maximum throughput, etc. This is captured by the set of equations (3).

When we refer to uncertainty in this paper we refer to the existence of uncertain model parameters. In the context of **(M1)**, for example, uncertainty may result from the fact that the importance weights of the different SQ dimensions, or the coefficients relating the operational variables to the SQ dimensions and to system characteristics, d, A, and B, respectively, can all realize, different values. Uncertainty can also be observed in the parameters of vector c, reflecting different stage characteristics, such as, for example, budget forecasts and capacity availability. (Note that uncertainty resulting from model misspecification is not addressed here.)

To capture uncertainty in **(M1)**, we introduce a set of scenarios $\Omega = \{1, 2, \ldots, S\}$. Following the RO approach described in Appendix A, we first identify among the set of operational variables x: (a) a subvector of operational variables x^d whose optimal values do not depend on the realizations of the uncertain parameters—in robust optimization terminology, these will be the *design* decision variables—and (b) a subvector of operational variables x^c. These will be the *control* variables as described in Appendix A, the optimal value of which will depend on the realization of uncertain parameters. With each scenario $s \in \Omega$, we associate the set $\{A_s, B_s, C_s, D_s,$ and $c_s\}$ of different values for the coefficients of the constraints and the objective function. We also introduce the probability of each scenario p_s, $\Sigma p_s = 1$, the sets of variables $\{z_1, z_2, \ldots, z_s\}$ and $\{\xi_1, \xi_2, \ldots, \xi_s\}$ to capture the infeasibility allowed in the constraints under scenario s, and finally, the set $\{x_1^c, x_2^c, \ldots, x_s^c\}$ for each scenario $s \in \Omega$. Note that as Mulvey et al. (1992) point out, control variables are subjected to adjustment once the uncertain parameters are observed. In the context of **(M2)**, however, if the uncertainty considered involves the parameters obtained from empirical models, as described later in §4, parameter uncertainty may never be completely resolved due to sampling error. The following robust optimization results:

(M2) $$\text{maximize} \quad \varphi(y_1, y_2, \ldots, y_s) - \lambda[\rho(z_1, z_2, \ldots, z_s, \xi_1, \xi_2, \ldots, \xi_s)] \tag{4}$$

$$\text{s. t.} \quad A_s x^d + B_s x_s^c + z_s = y_s \quad \text{for all } s \in \Omega, \tag{5}$$

$$E\ x^d = a \tag{6}$$

$$C_s x^d + D_s x_s^c + \xi_s = c_s \quad \text{for all } s \in \Omega, \tag{7}$$

$$x^d,\ x_s^c,\ y_s \geq 0 \quad \text{for all } s \in \Omega. \tag{8}$$

where,

x^d: the set of operational variables whose optimal values are not conditioned on the realization of the uncertain parameters.

x^c: the set of operational variables whose optimal values depend on the realization of the uncertain parameters.

$A_s, B_s,$
$C_s, D_s,$
c_s: uncertain parameters, and

a, E: fixed parameters.

Similar to **(M1)**, the set of equations (5) in **(M2)** relates SQ dimensions to operational variables x^d and x^c, under multiple scenarios s. The set of constraints (6) are the *structural* equations: These relate operational variables to system characteristics or constraints, and are free of noise. The set of constraints (7) also relates operational variables to system characteristics by allowing the existence of parameter uncertainty. In the presence of multiple scenarios, the first term in the objective value of **(M1)** becomes a random variable receiving the value $f(d_s^T y_s)$ with probability p_s. The choice of the function φ in **(M2)** maintains "solution robustness," that is, being close to optimality for any scenario realization. The second term $\rho(\cdot)$ in the objective function of **(M2)** is used to penalize violations of the constraints under some of the scenarios. This results in maintaining "model robustness," that is, being close to feasibility for any realization of s. The weight λ is used to trade off solution and model robustness. In the resulting goal programming formulation, as λ increases, the obtained solution will vary little with data perturbation, but this will occur at the expense of lower SQ. Finally, the choice of the penalty function ρ is problem dependent. For further discussion and suggestions for the penalty function ρ, as well as on the solution and model robustness trade-offs and on robust optimization in general, see Mulvey et al. (1995).

The generalization of **(M2)** to the multistage case is straightforward. SQ perceptions and operational variables from all stages $i = 1, 2, \ldots, N$ are required. Appendix B shows the resulting robust optimization formulation for the case when more than one stage is present and for a specific choice of the different functions involved.

In the next section, we demonstrate how the approach we present here can be applied in the important service area of health care.

4. An Application to Health Care

Before getting into the details of the application, it is useful to briefly review some recent service quality improvement efforts in health care.

4.1. Service Quality Efforts in Health Care

It is no secret that health care organizations are under extreme pressure to control costs and to provide high quality service at the same time. Indeed, patient satisfaction measures make up an important aspect of the structure of the Health Plan Employer Data and Information Set (HEDIS 2000), a recent set of health plan performance measures. Patient satisfaction efforts are also used by the Joint Commission on the Accreditation of Health Care Organizations in their accreditation reviews, which evaluate health care organizations. In a recent study, Roth et al. (1996) provide empirical evidence of the gap between patient and medical staff perceptions of hospital SQ. More specifically, they present a model that distinguishes between clinical quality (as judged by professionals) and SQ (as judged by patients) on realized health status and perceptions of service. The importance of improving SQ is further stressed as both outcomes are connected. Press et al. (1990) argue that sometimes actual healing may occur because of patient perceptions of the medical interaction. Other studies have shown a direct link between SQ and willingness to comply with a specific treatment regimen (Becker and Maiman 1975, 1980; Davis 1968), which in turn is linked to ultimate cost of care. Thus, it is likely that any effort to identify cost drivers of health care delivery will require a better understanding of the determinants of SQ in health care. Also, health care marketing research has shown that patient satisfaction with hospital services is positively associated with behavioral intentions to return to the hospital (Woodside et al. 1989).

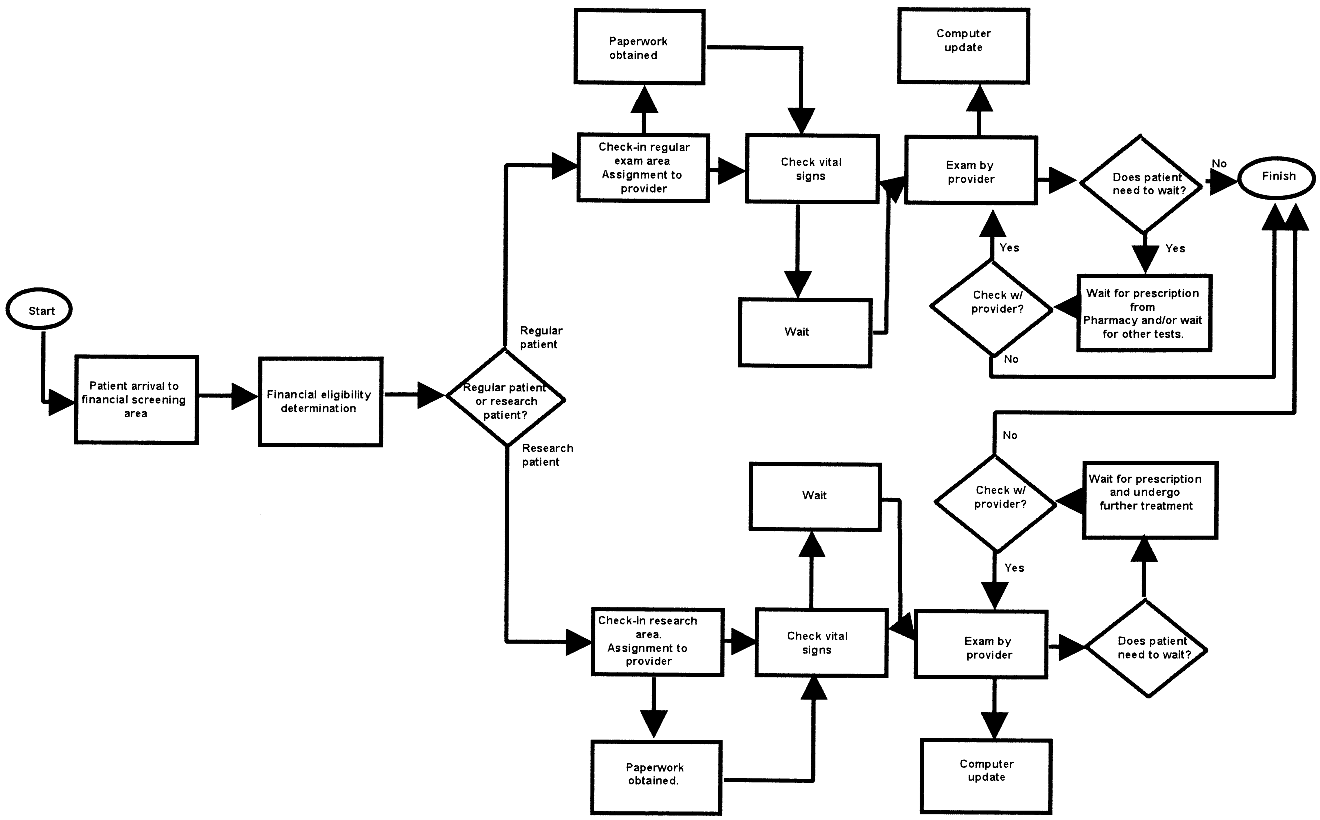
Many studies (Pascoe 1983, Aharony and Strasser 1993, Rubin 1990) summarize the recent literature on patient satisfaction and further point out the need to provide the researcher and practitioner with more useful information on how to improve the process. Furthermore, a number of studies have recently examined the adaptability of some of the SQ measurement approaches to the health care environment (Headley and Miller 1993, Reidenbach and Sandifer–Smallwood 1990, Schwartz and Brown 1989, Mowen et al. 1993, Peyrot et al. 1993).

Two key issues have not received much attention. One is the linkage between service delivery process characteristics and patient quality evaluations. The other is the need to examine individual service instances and match data from individual patients' perceptions with data describing the service process, at a microlevel. The approach followed in this study addresses both issues.

4.2. Research Design and Data Collection

The site where the study took place is an outpatient clinic of a large medical center located in the Southern California area. (For confidentiality purposes, some names and numbers have been disguised.) This is a high-volume clinic with more than 3,000 visits per month, whose patients are of medium to low socioeconomic background. Management developed an interest in applying our approach as part of the quality improvement and cost control efforts that had recently been initiated. The clinic is a classic example of a multistage service system in which patients visit several stages before departure. A typical visit proceeds as follows: After checking in at the receptionist area, patients visit the financial screening area, where financial eligibility is determined. They then proceed to the examination area, where vital signs are checked and a health care provider conducts an examination. When the examination is over, patients typically wait until prescriptions arrive from the pharmacy, which is located outside the building. We focused on the two main processing stages of the clinic in order to demonstrate the applicability of the SQ approach: the financial screening area and the examination area. The clinic also accepts research patients who undergo experimental treatment at a different area. Because of the heterogeneity of the procedures followed by research patients, these were not included in this study. A flowchart showing the main steps involved in these two areas is shown in Figure 1.

Figure 1 **Flowchart of the Major Steps Involved in the Financial Screening and the Examination Areas**



Data on relevant process operational variables and SQ perceptions were collected and matched for each of the two processing areas. Management played an important role in identifying relevant operational variables that drive SQ perceptions. The 3Ts framework (Chase and Stewart 1994) was also used as a guiding tool. Two types of ongoing voluntary training are provided to the clinic employees, namely, diversity training and service improvement training. The two programs are offered at different times of the year on a voluntary basis with a fixed cost associated with employee attendance. Both programs have been in place for a while, and were used as proxies of the *treatment* dimension of the 3Ts framework. Waiting times and incident duration were identified as operational variables under the *task* dimension. Under the 3Ts *tangible* dimension, variables included the cleaning frequency of the area of the incident and the cleaning frequency of the bathroom in the waiting area of the service incident. Information on the dimensions was gathered and matched to SQ information via an on line centralized computer information system, which maintains real-time information on the status of the patient's visit through the use of pen-like scanners.

A questionnaire based on SERVPERF (Cronin and Taylor 1992, 1994), which measured the expectations-perceptions gap directly for each item, was used. Face validity of the instrument used to collect SQ perceptions was further assessed a priori through discussions with the management of both the hospital and the clinic, as well as a number of interested physicians. A separate set of questions was made available for each processing stage. After discussions with management and the clinic's physicians we decided to discard certain items from the SERVPERF instrument that were not relevant to the health care environment (Babakus and Manegold 1992) or did not reflect the microlevel of analysis of this research. Out of the remaining 14 items for each area, 3 were reversed (see Appendix C). Additional questions were included to account for the impact of certain demographic and health status variables on the patients' SQ perceptions, as discussed in the patient satisfaction literature (Aharony and Strasser 1993). The receptionists administered the questionnaire to the patients upon arrival. The patients' identification number was printed on the questionnaire and the patients were instructed to complete the relevant part of the questionnaire after their experience with a certain area of the clinic was over. Completed questionnaires were returned in sealed boxes provided at the exit of the clinic.

During a seven–day pilot study, a total of 300 questionnaires was administered to patients and 122 were returned, a response rate of 40.1%. After interviewing patients who chose not to respond, or did not complete the questionnaire, a number of steps were taken to increase the response rate. Another version of the questionnaire in Spanish was constructed, since around 40% of the clinic's population are of Hispanic origin. Back translation maintained the validity of the instrument. Additionally, a letter from the clinic's administrative coordinator emphasizing the importance of the study and requesting the patient's cooperation was attached with every questionnaire.

A total of 850 questionnaires was administered between 10:00 a.m. and 3:00 p.m. over a period of six weeks. A response rate of 60.5% was obtained. Only fully completed questionnaires—a total of 149—from different patients were included in our study. At the end of each day, the identification number for each respondent was used to match the responses to stage operational variables. A list of the variables involved along with descriptive statistics is shown in Appendix D.

4.3. Data Analysis and Results

4.3.1. Implementing the Improvement Approach. Before proceeding with the approach implementation, SQ dimensionality was assessed using an exploratory principal components factor analysis of the SQ data obtained in the examination and financial screening areas. After oblique rotation, items loaded on four factors, as shown in Table 1. Three of the dimensions identified correspond to the dimensions of responsiveness, tangibles, and empathy suggested by Parasuraman et al. (1985, 1986, 1994). The remaining five items, which correspond to the dimensions of reliability and assurance as identified by Parasuraman et al., loaded on a single dimension, will henceforth be referred to as R/A. A single composite indicator for each dimension was constructed, reflecting the average score of all items included in that dimension. Reliability of the items for the different subscales was also assessed. Cronbach coefficients and the item–to–total correlations are shown in Table 2.

Table 1 Principal Components Factor Loadings (Oblique Rotation)

Item	I	II	III	IV
1	**0.42**	0.12	0.28	0.17
2	**0.46**	0.23	0.11	0.16
3	**0.33**	0.28	0.13	0.13
4	0.25	**0.66**	0.05	0.04
5	0.22	**0.42**	0.12	0.07
6	0.28	**0.44**	0.14	0.02
7	0.11	0.14	**0.38**	0.17
8	0.20	0.11	**0.58**	0.14
9	0.26	0.02	**0.54**	0.23
10	0.28	0.04	0.15	**0.35**
11	0.22	0.12	0.11	**0.44**
12	0.13	0.14	0.24	**0.52**
13	0.17	0.15	0.16	**0.39**
14	0.29	0.03	0.19	**0.32**

Loadings >0.3 are shown in bold. All interfactor correlations <0.30, except II–III, 0.42.

Linear regression models were constructed for the different SQ dimensions across the two stages. Demographics, health indicators, and operational variables guided by the health care marketing literature and the 3Ts framework were considered as possible regressors for each model. An all–possible–subsets regression approach that gave us total control on variable selection was followed, in an attempt to develop parsimonious models that explain as much variability in the SQ dimensions as possible, and to minimize specification error in the development of the models. Each model underwent extensive diagnostic checking to ensure that all classical regression assumptions were satisfied. The

Table 2 Subscale Item–to–Total Correlations, Cronbach Alpha Reliability Coefficients, Item Means, and Standard Deviations

	Item-to-Total Correlations	Mean	SD
(TANG) α = **0.783**			
1. The provider was neatly and appropriately dressed	0.606	4.76	0.43
2. The examination area was clean and pleasing	0.532	4.67	0.65
3. Signs and decorations in the examination area were appropriate	0.643	4.37	0.62
TANG Composite Index		**4.6**	**0.57**
(RESP) α = **0.867**			
4. You did not have to wait to see the provider	0.689	4.72	0.52
5. The time it took to complete the examination was reasonable	0.807	4.39	0.76
6. The provider was not willing to help you	0.753	2.72	0.69
RESP Composite Index		**4.46**	**0.66**
(EMP) α = **0.655**			
7. The provider gave you individual and personal attention	0.675	4.56	0.98
8. The provider was not sensitive to your individual problems	0.873	2.35	0.88
9. The provider had your best interest at heart	0.698	4.87	0.78
EMP Composite Index		**4.69**	**0.88**
(R/A) α = **0.818**			
10. The provider explained well what he/she was doing	0.756	4.59	0.88
11. The provider was not courteous	0.743	2.21	0.89
12. The provider showed sincere interest in answering any of your questions	0.334	4.66	1.01
13. The provider was competent	0.708	4.88	0.78
14. The provider instilled confidence in you	0.890	4.78	0.83
R/A Composite Index		**4.74**	**0.88**

models and OLS regression results are shown in Table 3. Relative importance weights for each service stage, as well as for each SQ dimension of each stage, were also calculated, as shown in Table 4.

To proceed with the development of optimization models, relevant constraints were first identified. Current practice, for example, requires at least two physicians to be present in the examination area at any given time. Other types of providers, such as nurses, physicians, or nurse practitioners, can also be used to treat patients. Given the number of available examination spaces, the clinic can accommodate up to 20 providers. Additional constraints may include yearly training and everyday operational budget limitations, as well as the clinic's minimum daily capacity.

Table 5 presents the formulation of **(M1)** in the examination area. The objective function is a weighted sum of the different SQ dimensions, where the weights represent the importance given to each dimension. Equations (9)–(12) relate the SQ dimensions with operational variables for each stage. These, along with Equations (14)–(16), are empirically determined. Constraints (18) and (19) refer to the yearly training and daily operational budget, respectively. The remaining constraints reflect the physical limitations of the system. Finally, constraint (20) reflects the capacity requirement of each stage where the parameter δ corresponds to the expected maximum number of patients daily.

Table 6 provides solutions to this optimization model when mean values of the model parameters are used, assuming no parameter uncertainty. Target SQ levels along with specific recommendations for improvement are shown. Also shown in Table 6 are results from a different formulation, where the objective is to minimize operating and training costs while maintaining the same level of service quality. This formulation emerged from extensive discussions with the management of the clinic, who expressed an interest in examining the various cost inefficiencies—both in

Table 3 OLS Models and Empirical Results for the Examination and Financial Screening Stages

Models

Examination Area						
(1) R/A	$= b_0$	$+ b_1$ SITrain	$+ b_2$ CDTrain	$+ b_3$ AGE	$+$	b_4 PROF
(2) RESP	$= b_0$	$+ b_1$ DURATION	$+ b_2$ WAIT	$+ b_3$ HEALTH		
(3) EMP	$= b_0$	$+ b_1$ DURATION	$+ b_2$ WAIT	$+ b_3$ SITrain	$+$	b_4 CDTrain
(4) TANG	$= b_0$	$+ b_1$ BATHtime	$+ b_2$ MOPtime			
(5) WAIT	$= b_0$	$+ b_1$ (1/k)				
(6) BATHtime	$= b_0$	$+ b_1$ BATH				
(7) MOPtime	$= b_0$	$+ b_1$ MOP				
Financial Screening Area						
(8) R/A	$= b_0$	$+ b_1$ SITrain	$+ b_2$ CDTrain	$+ b_3$ AGE	$+$	b_4 PROF
(9) RESP	$= b_0$	$+$ *b*1 DURATION	$+ b_2$ WAIT			
(10) EMP	$= b_0$	$+ b_1$ DURATION	$+ b_2$ WAIT	$+ b_3$ SITrain	$+$	b_4 CDTrain
(11) TANG	$= b_0$	$+ b_1$ BATHtime	$+ b_2$ MOPtime			
(12) WAIT	$= b_0$	$+ b_1$ (1/k)				
(13) BATHtime	$= b_0$	$+ b_1$ BATH				
(14) MOPtime	$= b_0$	$+ b_1$ MOP				

OLS Results for Examination Area

Variable	R/A (Model 1)	RESP (Model 2)	EMP (Model 3)	TANG (Model 4)	WAIT (Model 5)	BATHtime (Model 6)	MOPtime (Model 7)
Intercept	4.13***	6.81*	3.86*	6.19*	−114.00***	227.76*	175.67*
	(0.85)	(3.35)	(1.47)	(2.92)	(32.95)	(112.75)	(65.55)
SITrain	0.04*		0.04**				
	(0.01)		(0.01)				
CDTrain	0.06**		0.07**				
	(0.02)		(0.02)				
AGE	0.01*						
	(0.003)						
PROF	0.016*						
	(0.01)						
DURATION		−0.02*	0.02**				
		(0.01)	(0.01)				
WAIT		−0.03***	−0.01**				
	(0.01)	(0.003)					
HEALTH		0.17***					
	(0.05)						
BATHtime				−0.01**			
				(0.002)			
MOPtime				−0.01***			
				(0.001)			
BATH						−45.15**	
						(16.60)	
MOP							−40.55**
							(13.43)
1/k					2277**		
					(807.45)		
F value	**45.82**	**93.82**	**44.00**	**57.36**	**298.45**	**492.13**	**378.00**
R^2_{adj}	**0.56**	**0.66**	**0.55**	**0.44**	**0.67**	**0.77**	**0.72**

OLS Results for Financial Screening Area

Variable	R/A (Model 8)	RESP (Model 9)	EMP (Model 10)	TANG (Model 11)	WAIT (Model 12)	BATHtime (Model 13)	MOPtime (Model 14)
Intercept	3.89***	6.86*	2.73*	6.20*	33.13**	216.45*	184.22*
	(0.83)	(3.25)	(0.59)	(2.80)	(8.50)	(103.07)	(90.75)
SITrain	0.04**		0.06***				
	(0.01)		(0.02)				
CDTrain	0.04***		0.04*				
	(0.01)		(0.02)				
AGE	0.004*						
	(0.002)						
PROF	0.01**						
	(0.04)						
DURATION		−0.02***	0.0585*				
		(0.01)	(0.0229)				
WAIT		−0.03***	−0.004**				
		(0.01)	(0.001)				
HEALTH							
BATHtime				−0.01*			
				(0.002)			
MOPtime				−0.01***			
				(0.002)			
BATH						−48.75**	
						(17.92)	
MOP							−48.34**
							(−16.50)
1/k					−3.15**		
					(1.13)		
F value	**44.65**	**129.78**	**29.45**	**67.38**	**261.33**	**553**	**441**
R^2_{adj}	**0.56**	**0.64**	**0.45**	**0.48**	**0.64**	**0.79**	**0.75**

Notes: Numbers indicate regression coefficients. Numbers in parentheses indicate standard errors. Insignificant coefficients ($p > .05$) are not shown. Detailed variable definitions are given in Appendix D. The models were chosen based on their R^2, standard errors, and C_p values, on the diagnostic checks for model assumptions, but also on the interpretability of the results, which was assessed via discussions with the management of the clinic. No hold-out sample was employed; thus, we leave it to future research to replicate the final regression results. A Chow test for parameter stability was also used to assess whether the resulting regression equations for each SQ dimension were different across stages. The test was significant ($p < .05$) in all cases, suggesting that SQ drivers and their impact do differ across stages.
*Significant at the .05 level
**Significant at the .01 level
***Significant at the .001 level

the yearly training budget and the daily operational budget—given the current level of service quality.

4.3.2. Incorporating the Impact of Uncertainty. The parameters of the model presented in Table 5 can be divided into two main categories: those that are fixed and demonstrate no uncertainty, such as, for example, certain system limitations, and those that can exhibit uncertainty. The latter category can be further divided into two subcategories: (a) parameters that exhibit uncertainty originating from sources other than empirical estimation, including those based on management's intuition or other information obtained by management (e.g., budget estimates, etc.); (b) parameters that are empirically determined based on regression estimates, such as, for example, the objective function coefficients.

First, we provide a simple example to demonstrate the impact of uncertainty originating from this first

Table 4 Relative Importance Weights Obtained for Each SQ Dimension at Each Stage*

	Importance Weight	
SQ Dimension	Examination Area	Financial Screening
R/A	0.34	0.25
RESP	0.33	0.41
EMP	0.23	0.23
TANG	0.08	0.10

*Importance weights were obtained by considering the standardized regression coefficients, when the composite scores for the different dimensions were regressed against the overall quality score for each stage.

category of parameters on the model's solution. We allow uncertainty in two parameters, the training and operating budgets, each taking one of three possible scenarios. Management provided estimates of these parameters along with probability estimates for the occurrence of each scenario. Table 7 presents a sensitivity analysis of nine such scenarios for the formulation of Table 9. We observe that the level of SQ varies anywhere from 4.94 to 6.1.

A Bayesian framework can be used to generate uncertainty scenarios for those parameters of Table 5, which are estimated through the use of regression models. More specifically, such scenarios can be based on the posterior distribution of the regression model parameters. Here, a prior distribution for the parameters is specified, and then the posterior distribution can be calculated from the data. In the case where the prior variances of the theoretical parameters are very large, the posterior distribution of the parameters can be approximated by the normal distribution whose mean and variance coincide with those of the observed classical regression estimates (Hamilton 1994). Thus, given that the regression assumptions are satisfied and that little prior information is available on the parameters, the distribution of each estimate can be used to provide reasonable scenarios for each estimate. Based on the above, we next describe a heuristic approach that can be followed to generate scenarios and associated probabilities in the presence of noninformative priors. We point out, however, that if information on the prior distribution of the coefficients does exist, then the scenario generation process should be based on the posterior distribution of the estimates, calculated in a Bayesian framework.

Our heuristic approach uses the distribution of the regression parameter estimates to generate the scenarios, as shown in Figure 2. For demonstration purposes, we will show how three different scenarios can be generated for each regression coefficient shown in the optimization model of Table 5. The distribution of each regression estimate is divided into six areas, ranging from one to three standard deviations (σ) from the mean. The first scenario corresponds to the expected value of the estimate, with probability equal to the area under $\pm 1\sigma$ from the mean. This also defines the most probable scenario. The other two scenarios for each coefficient correspond to the values that find themselves $+2\sigma$ and -2σ away from the mean. Their probability equals to the area under the normal curve, between $+1\sigma$ and $+3\sigma$, and -1σ and -3σ, respectively. Following this approach, additional scenarios representing different realizations of the parameters can be created. This must be done with caution, however, since as the number of different scenarios for each coefficient increases, the number of decision variables expands rapidly.

Tables 8 and 9 present robust optimization results when three scenarios were used for each of the uncertain parameters of the model shown in Table 5. In the resulting robust optimization model, equations (17) of Table 5, for example, can be thought of as the "structural" constraints—following the terminology by Mulvey et al.—containing the design variables. These maintain some level of the number of different types of providers regardless of parameter uncertainty. The overall quality level of the examination area is shown for different choices of the RO weight λ. Clearly, as the value of λ increases, the expected value of SQ decreases. Also shown is the sum of all errors (positive and negative slacks) for the budget constraints associated with all scenarios for each choice of λ. As the value of λ increases, the obtained solutions are less sensitive to data perturbations.

A similar approach can also be followed for the financial screening stage. Considering each stage separately, however, may lead to subsystem optimization,

Table 5 Optimization Model Formulation (Maximizing SQ) in the Examination Area

Max 0.34 R/A + 0.33 RESP + 0.23 EMP + 0.08 TANG	(8)
where	
R/A = 4.12 + 0.03 SITrain + 0.05 CDTrain + 0.01 AGE + 0.02 PROF	(9)
RESP = 6.81–0.02 DURATION − 0.03 WAIT + 0.16 HEALTH	(10)
EMP = 3.86 + 0.02 DURATION–0.01 WAIT + 0.04 SITrain + 0.07 CDTrain	(11)
TANG = 6.20–0.01 BATHtime–0.01 MOPtime	(12)
subject to	
k = MD + PA + NP + NURSE	(13)
WAIT = −114 + 2277 (1/k)	(14)
BATHtime = 227.76–45.15 BATH	(15)
MOPtime = 175.67–40.55 MOP	(16)
8 ≥ MD ≥ 2, k ≤ 20, PA, NP ≤ 3	(17)
\$90 k (SITrain) + \$70 k (CDTrain) ≤ 25000	(18)
\$310.14 MD + \$96 PA + \$148.64 NURSE + \$120 NP + \$12.80 BATH + \$8.40 MOP ≤ 3000	(19)
(480min/16.94) k ≥ δ, and	(20)
7 ≥ EMP, TANG, RESP, R/A ≥ 0	(21)

as we discuss in the next section. The general formulation of Appendix B is designed to capture stage interactions. Table 10 presents a formulation that considers both stages simultaneously. Tables 11 and 12 present the corresponding robust optimization results for the formulation that considers both stages.

4.4. Discussion

We next provide a discussion of some managerial insights obtained from the empirical application.

4.4.1. SQ Drivers: Empirical Evidence. A novel characteristic of our approach is the examination of service quality at the level of the individual stage. According to the general director of the clinic, this study not only provided a number of new insights regarding the improvement of service quality, but also provided the spark for further examination and further improvement of the service delivery system. Upon completion of the study, an assessment team made up of a number of doctors, top management members, and the researchers, was put together to critically assess the usefulness of its findings.

The results of Table 4, regarding the importance of different SQ dimensions at each stage, suggest that SQ should indeed be examined at levels lower than that of the organization. The importance given to different SQ dimensions varies from stage to stage. For example, waiting may not be perceived as important when anticipating a surgical procedure, but can be very important when in line simply to check in. Although this information only confirmed the team's understanding of the system, it adds to the increasing body of literature that focuses on examining SQ at such micro-levels (Rust et al. 1994).

Regarding the dimensionality of SQ, the findings support only four SQ dimensions. More specifically, the items corresponding to the dimensions of reliability and assurance loaded on the same factor. Conflicting results regarding the dimensionality of SQ have been reported in the health care marketing literature (Headley and Miller 1993, Reidenbach and Sandifer-Smallwood 1990, Schwartz and Brown 1989, Mowen et al. 1993, Peyrot et al. 1993) and elsewhere (Babakus and Boller 1991, Carman 1990). Parasuraman (1991) discusses in more detail such variation in SQ dimensionality, which may depend on the data collection and/or analysis procedures used. Indeed, the general consensus of the team was that this result may be attributed to the clinic's population, which consisted of patients of low socioeconomic background with limited ability to assess technical quality (Harvey 1998). In general, the dimensionality of SQ at a lower level of analysis deserves further investigation.

The results from the regression models shown in Table 3 revealed some of the drivers of the different SQ

Table 6 **Solution of the Optimization Models of the Examination Area—No Parameter Uncertainty Is Assumed**

*Maximize Customers' Perceptions Subject To Budget Limitations**

	Current Level	Best Allocation
QUAL	5.09	5.92
Training Cost ($/year)	0642.16	25000.00
Daily Cost ($/day)	2357.10	3000.00
SITrain	5.73	5.48
CDTrain	3.73	12.00
K	13.7	18.8
MD	3.2	2.2
PA	3.0	3.0
NURSE	4.5	10.6
NP	3.0	3.0
BATH	2.3	5.0
MOP	2.1	4.3

Minimize Costs for Given Level of SQ[a]

	Current Level	Best Allocation if Yearly Training Budget is Kept at Current Level	Best Allocation if Average Daily Budget Is Kept at Current Level
QUAL	5.09	5.09	5.09
Training Cost	10642.16	10642.16	1784.40
Daily Cost	2357.10	2025.40	2357.10
SITrain	5.73	19.47	0.00
CDTrain	3.73	12.00	1.74
k	13.7	12.4	14.6
MD	3.2	2.0	2.0
NURSE	4.5	4.4	6.6
BATH	2.3	5.0	5.0
MOP	2.1	4.3	4.3

*Current SITrain and CDTrain cannot exceed 24 and 12 days per year, respectively; current available daily operating budget is $3,000/day; training budget is $25,000/year.

dimensions for each stage and provided a number of important new insights into the management of the clinic. Such models can be used to establish functional relationships between the operational variables and SQ dimensions, but also to point toward where and how to improve SQ. An important observation, which elicited considerable discussions among the assessment team, was that the resulting models differ among stages. Different SQ drivers exist across stages, and whenever such drivers are the same, the corresponding relationship between drivers and SQ—as evidenced by the magnitude of the regression coefficients—differs. Management, for example, had no information on the impact of the different training programs on SQ perceptions. As evident from the results of Table 3, CDTrain appears to have greater impact than Sitrain on the dimensions of R/A and RESP in the examination area, but the same does not hold in the financial screening area. The importance of CDTrain is further stressed by the findings of Table 4, which suggest that the dimensions of R/A and RESP are indeed the most important in the examination area.

The differences across the models of the two stages provided a number of further important insights, which were new to management. Consider, for example, the variable HEALTH, which, although a significant driver of responsiveness in the examination area, was not deemed significant in the corresponding model of the financial screening area. It was well known to the team that the status of a patient's health does matter in SQ evaluations. However, these findings suggest that this may not be important for stages such as the financial screening area, and thus, special attention to the health status of patients may only be required in the examination area.

Other examples of findings that the team considered important were the inclusion in the regression models of the patients' age ($p < .01$) in both stages, a result consistent with the health care literature in which increased service satisfaction is reported to be associated with being older (Pascoe 1983). The type of health care provider was not included in the regression models ($p > .05$). This finding suggests that the type of health care provider (medical doctor, physician assistant, nurse, or nurse practitioner) might not play an important role in determining SQ perceptions. As counterintuitive as this appears, this result did not surprise the practitioners of the team. Patients, given their socioeconomic background, may have difficulty differentiating between the various types of providers. (It is emphasized that this study focused on SQ perceptions alone, and ignored clinical outcomes, which may vary greatly from provider to provider.)

Table 7 Sensitivity Analysis for the Optimization Model (Maximizing SQ) of the Examination Area

Scenario	Train Cost (dollars)	Probability	Daily Cost (dollars)	Probability	Scenario Probability
1	25,000	0.5	1,500	0.2	0.1
2	25,000	0.5	2,000	0.3	0.15
3	25,000	0.5	3,000	0.5	0.25
4	30,000	0.3	1,500	0.2	0.06
5	30,000	0.3	2,000	0.3	0.09
6	30,000	0.3	3,000	0.5	0.15
7	35,000	0.2	1,500	0.2	0.04
8	35,000	0.2	2,000	0.3	0.06
9	35,000	0.2	3,000	0.5	0.1

Scenario	1	2	3	4	5	6	7	8	9
QUAL	4.94	5.45	5.92	5	5.58	6.01	5	5.72	6.1
Train $	25k	25k	25k	30k	30k	30k	35k	35k	35k
Daily $	1,500	2,000	3,000	1,500	2,000	3,000	1,500	2,000	3,000
SITrain	21.96	13.36	5.48	24	17.9	8.44	24	22.44	11.4
CDTrain	12	12	12	12	12	12	12	12	12
K	8.87	12.3	18.7	8.87	12.2	18.7	8.87	12.23	18.7
BATH	5.04	5.04	5.04	5.04	5.04	5.04	5.04	5.04	5.04
MOP	4.33	4.33	4.33	4.33	4.33	4.33	4.33	4.33	4.33

Figure 2 Scenario Generation of Empirically Determined Regression Coefficients

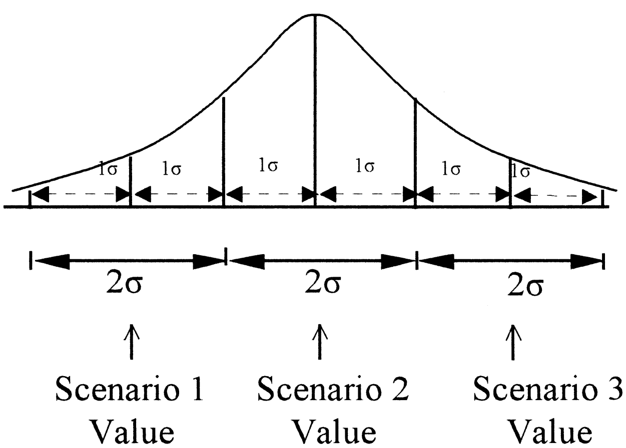


Table 8 Robust Optimization Results (Maximizing SQ) of the Examination Stage: Overall Quality Levels for Different Values of λ, and Sum of Absolute Values of Error Observed in the Cost Constraints

Robust Optimization Weight λ	Overall Quality Level	Absolute Error Observed in Training Budget Constraint
0.0	5.65	68,564.8
0.001	5.63	65,735.6
0.002	5.55	57,553.9
0.003	5.53	53,978.3
0.004	5.42	51,356.7
0.005	5.05	46,856.7
0.006	5.01	44,889.9
0.007	4.98	43,167.5

4.4.2. Optimization Models: Managerial Implications. The application of the third step of our approach gave rise to interesting insights related to how robust optimization models can be set up to overcome variability of parameter specification while capturing stage interactions, and how practicing managers can use such models in their decision making.

Overcoming Variability in Parameter Specification and Capturing Stage Interactions. Consider, for example, the results of the optimization formulation for the examination area shown in Table 6, where it is demonstrated that management can improve customers' perceptions of SQ (from 5.09 to 5.92) through a number of actions. These actions include increasing the

Table 9 Solution to the Robust Optimization of the Examination Stage (Maximizing SQ) Obtained by Using $\lambda = 0.003$ and a Quadratic Penalty Function $\Sigma_{s \in \Omega'} z_s^t z_s$, in the Objective Function

Variable	Optimal Solution
QUAL	5.53
SITrain	14.4
CDTrain	12.0
K	13.1
BATH	5.0
MOP	4.3

current amount spent on training and daily expenses, increasing the average daily number of providers to 18.75 (from 13.7)—which could result in a decrease of the long waiting times—and increasing the frequency of cleaning. The results of Table 6 also suggest that for the current levels of quality, the clinic could be spending much less in either training or daily costs. If we kept training costs at the current level, the average number of providers could decrease while maintaining the same level of quality. Some adjustment on the amounts of training is also required, since CDTrain is more effective and less expensive than SITrain.

The above recommendations are, however, myopic in at least two ways: (a) they do not consider model parameter uncertainty, and (b) they ignore interactions with other stages. The solution to the robust optimization formulation for the examination area, shown in Tables 8 and 9, overcomes the first limitation by proactively considering parameter uncertainty at the examination area. Given the uncertainty of the different model parameters, the solution suggested in Table 9 provides a quality level that is not much lower than that of Table 6—when no uncertainty was assumed—in the expense of model robustness. Thus, given the different possibilities of the model's parameters, the solution suggested focused on improving the levels of training, and not on increasing the number of service providers. In other words, given the existence of different possibilities for the various model parameters, management should pay more attention to improving the levels of training according to the suggestions in Table 9. Regardless of the different parameter realizations, following these suggestions can ensure no major deviations from the optimal quality level reported in Table 6.

However, the solution suggested in Tables 8 and 9 does not overcome the second limitation of ignoring interactions with other stages, since optimizing individual stages separately can result in sub-optimization. This second limitation is addressed by the formulation of Table 10, which, in turn, is based on the general formulation shown in Appendix B. To obtain the corresponding robust optimization solutions shown in Tables 11 and 12, the objective function was modified to reflect a weighted sum of the SQ perceptions in both stages; the weights represent the importance patients give to each stage. Other models to minimize operating and/or training costs while maintaining some level of SQ can also be formulated in a similar manner.

Note that when both stages are considered while taking into account parameter uncertainty, the solution for the examination area changes dramatically. More specifically, given parameter uncertainty in both stages, the model suggests an increase in the number of health care providers in the examination area and a corresponding decrease in the number of providers in the financial screening area. It is also clear from the model's suggestion that it places more "value" on the ability of CDTrain to improve SQ perceptions when compared to that of SITrain. The model simply recognizes the fact that this type of training should be encouraged, given that it can further improve SQ and that budget for such an action is also available. What the model cannot capture is the voluntary nature of attendance when seminars are offered. In fact, such training was only introduced a few months before the study took place, and, although voluntary in nature, it has recently started to become popular among personnel. Thus, given the model's recommendations, the service manager is expected to provide additional encouragement to the clinic's personnel to attend such training seminars. The overall quality level that can be achieved when both stages are considered is higher than the level achieved if each stage is considered separately.

We further point out that a good solution to the robust optimization formulation depends on the choice of an appropriate value of the weight λ, which is used to derive a set of solutions that are progressively more

Table 10 Optimization Model (Maximizing SQ) That Captures Both the Examination and the Financial Screening Areas

$$\text{Max } w_1{*}(0.25{*}\text{R/A}_1 + 0.41{*}\text{RESP}_1 + 0.23{*}\text{EMP}_1 + 0.10{*}\text{TANG}_1) + w_2{*}(0.34{*}\text{R/A}_2 + 0.33{*}\text{RESP}_2 + 0.23{*}\text{EMP}_2 + 0.08{*}\text{TANG}_2) \tag{22}$$

where

$$\text{R/A}_1 = 4.13 + 0.04{*}\text{SITrain}_1 + 0.06{*}\text{CDTrain}_1 + 0.01{*}\text{AGE} + 0.02{*}\text{PROF}_1 \tag{23}$$
$$\text{RESP}_1 = 6.81 - 0.02{*}\text{DURATION}_1 - 0.03{*}\text{WAIT}_1 + 0.17\ \text{HEALTH}_1 \tag{24}$$
$$\text{EMP}_1 = 3.86 + 0.02{*}\text{DURATION}_1 - 0.01{*}\text{WAIT}_1 + 0.04{*}\text{SITrain}_1 + 0.07{*}\text{CDTrain}_1 \tag{25}$$
$$\text{TANG}_1 = 6.19 - 0.01\ \text{BATHtime}_1 - 0.01{*}\text{MOPtime}_1 \tag{26}$$
$$\text{R/A}_2 = 3.88 + 0.04{*}\text{SITrain}_2 + 0.04{*}\text{CDTrain}_2 + 0.01{*}\text{AGE} + 0.02{*}\text{PROF}_2 \tag{27}$$
$$\text{RESP}_2 = 6.86 - 0.02{*}\text{DURATION}_2 - 0.03{*}\text{WAIT}_2 \tag{28}$$
$$\text{EMP}_2 = 2.73 + 0.06{*}\text{DURATION}_2 - 0.03{*}\text{WAIT}_2 + 0.06{*}\text{SITrain}_2 + 0.04{*}\text{CDTrain}_2 \tag{29}$$
$$\text{TANG}_2 = 6.20 - 0.01\ \text{BATHtime}_2 - 0.01{*}\text{MOPtime}_2 \tag{30}$$

subject to

$$k_1 = \text{MD} + \text{PA} + \text{NP} + \text{NURSE} \tag{31}$$
$$k_1 \le 20 \tag{32}$$
$$\text{PA, NP} \le 3 \tag{33}$$
$$8 \ge \text{MD} \ge 2 \tag{34}$$
$$k_2 \le 10 \tag{35}$$
$$\text{WAIT}_1 = -33.13 - 3.15{*}k_1 \tag{36}$$
$$\text{WAIT}_2 = -114 + 2277{*}(1/k_2) \tag{37}$$
$$\text{BATHtime}_1 = 227.76 - 45.15{*}\text{BATH}_1 \tag{38}$$
$$\text{MOPtime}_1 = 175.67 - 40.55{*}\text{MOP}_1 \tag{39}$$
$$\text{BATHtime}_2 = 216.45 - 48.74{*}\text{BATH}_2 \tag{40}$$
$$\text{MOPtime}_2 = 184.22 - 48.34{*}\text{MOP}_2 \tag{41}$$
$$\$90{*}k_1{*}\text{SITrain}_1 + \$70{*}k_1{*}\text{CDTrain}_1 + \$90{*}k_2{*}\text{SITrain}_2 + \$70{*}k_2{*}\text{CDTrain}_2 \le \theta_1 \tag{42}$$
$$\$310.14{*}\text{MD} + \$96{*}\text{PA} + \$148.64{*}\text{NURSE} + \$120{*}\text{NP} + \$12.80{*}\text{BATH}_1 + \$8.40{*}\text{MOP}_1 + \$72.1{*}k_2 + \$12.80{*}\text{BATH}_2 + \$8.40{*}\text{MOP}_2 \le \theta_2 \tag{43}$$
$$(480\text{min}/13.60){*}k_1 \ge \delta \text{ and}$$
$$(480\text{min}/16.94){*}k_2 \ge \delta \tag{44}$$
$$7 \ge \text{EMP}_1, \text{TANG}_1, \text{RESP}_1, \text{R/A}_1, \text{EMP}_2, \text{TANG}_2, \text{RESP}_2, \text{R/A}_2 \ge 0 \tag{45}$$

where, w_1: importance weight of stage $i = 1$ (the financial screening area).
w_2: importance weight of stage $i = 2$ (the examination area).
θ_2, θ_2: parameters reflecting training and operational budgets.

"robust" to data perturbations at the expense of the objective value. As λ increases, the expected SQ value decreases, but the solution becomes more robust in its accommodation to possible changes of the model's parameters. Given the information in Table 11, a good choice would be a value of $\lambda = 0.003$, since, for this value, the solution of the resulting optimization problem remains close to the optimal, while the reported error associated with the budget constraints is low. The reported error here is the sum of the absolute values of the positive and negative slacks from all resulting scenarios associated with the budget constraints.

Using RO Findings for Managerial Decision Making. The results from the optimization models were discussed extensively by the assessment team in a series of meetings, and they triggered a detailed examination of both stages. When evaluating the results from the optimization model, the general consensus was that the robust optimization model can provide useful and solid guidelines for the improvement of service quality. The model not only confirms that high levels of training and the number of medical providers do matter, but it also makes solid and reasonable suggestions on what these levels should be given the realities of the clinic. As such, it was decided that this model should be used along with existing models for staffing, training, and other operational decisions currently in place.

During the discussions, a number of issues were

Table 11 Robust Optimization Results for Both Stages (Maximizing SQ): Overall Quality Levels for Different Values of λ and Sum of Absolute Values of Error Observed in the Cost Constraints

Robust optimization weight λ	Overall quality level	Absolute error observed in training budget constraint
0.0	5.79	77,324.7
0.001	5.76	75,922.8
0.002	5.74	73,628.2
0.003	5.73	67,917.1
0.004	5.55	61,241.8
0.005	5.18	58,877.2
0.006	4.95	56,388.6
0.007	4.83	55,881.4

Table 12 Solution to the Robust Optimization for Both Stages (Maximize SQ) Obtained by Using $\lambda = 0.003$

Variable	Optimal Solution
QUAL	5.73
Examination area	
SITrain	3.85
CDTrain	12.00
K	17.15
BATH	5.04
MOP	4.33
Financial Screening area	
SITrain	12.00
CDTrain	12.00
K	2.00
BATH	4.44
MOP	4.92

raised, the most important of which were the following: (a) Are there other drivers of SQ, such as, for example, the type of technology used, that were not considered in this application? (b) How can we generate reliable scenarios for the RO model? (c) Finally, how can this model be expanded to include more stages and multiple objectives, such as technical quality (clinical outcomes)? It was decided that hospital teams consisting of management and medical staff be formed, with inputs from the researchers, to address the above issues. These teams would have a problem-solving orientation, and would fit well within the framework of the quality program recently initiated at the hospital. One of the suggestions was to use a Delphi approach to generate scenarios for some of the uncertain parameters, such as budget estimates. Focus groups and projective techniques, including patients and providers, could be used to identify further drivers of SQ. (The research team is currently exploring the use of multiobjective programming to expand the scope of the developed model to include more objectives.)

5. Limitations and Future Research

The SQ improvement approach presented in this paper provides solid direction toward making cost-quality trade-offs in services. However, it comes with certain limitations. We next provide a brief summary of a number of issues that need further consideration.

First, the linkage of SQ perceptions to process operational variables described in Steps 1–3 of the approach is static in nature. Future research needs to incorporate the dynamic aspects of the proposed approach, such as the frequency of data collection and model building. The examination of multiobjective programming along with RO, which could incorporate the existence of additional non–SQ performance measures, would be of great value.

Second, an implicit assumption of the optimization models of Step 3, as demonstrated in the empirical study of §4, is a linear relationship between process operational variables and SQ perceptions, and between SQ dimensions and overall SQ. Such linear relationships may not hold up in practice. Thus, specifying the exact nature of such relationships is important to enhancing the realism of such models. Also, examining different approaches for establishing the functional relationships between operational variables and SQ quality perceptions, e.g., nonparametric approaches, would be of value.

Third, we note again that the empirical study we presented in §4 was conducted in a single health care facility. Thus, some of the results, such as the dimensionality of SQ or the inability of customers to differentiate between service providers, may be specific to the particular service setting. We further point out that the focus of the study was on SQ perceptions and not on technical quality, i.e., clinical outcomes, although the two are related (Roth et al. 1996).

Fourth, the choice of relevant operational variables still poses a challenge. Indeed, while the 3Ts conceptual framework provides a useful starting point to identify such variables, it deserves further empirical investigation. What are other important operational dimensions that should be considered? Can a holistic framework to help identify relevant operational characteristics in different settings be developed? The choice of such variables can come from expert practitioner teams that are well aware of the operations of each stage. Information from external and internal customers through focus groups, thematic apperception tests, and other exploratory research techniques can also provide valuable help in this direction.

Fifth, the results of the RO models presented here deserve further validation. Although this paper does provide an approach to generate scenarios of empirically determined parameters in RO, our strategy was to use a small set of scenarios to demonstrate the applicability of RO models in a real service setting. A more complete analysis, which will take into account a large number of different scenarios, is needed. Of course, as the number of scenarios increases, so does the complexity and the computational difficulty of the resulting formulations. This issue, however, is becoming less critical as more powerful computers and highly efficient algorithms become available. As resulting RO problems increase in size, special purpose algorithms appear in the literature for their solution. (See Mulvey et al. 1995, for a discussion of existing special purpose algorithms, which exploit novel architectures of high performance computers to solve robust optimization problems with a large number of scenarios.) In addition, the choice of different scenarios still presents a major challenge in RO. Further work is also required on the choice of the goal programming parameter λ, which appears in the objective function of the RO model. While a good value of λ usually can be determined empirically, no a priori formal mechanism for selecting it has been determined.

Sixth, one of the underlying assumptions of the models presented in the previous section is that the relationships established among the different dimensions of SQ and the different operational characteristics are causal. This is indeed a strong assumption, which cannot be supported by observational data alone. If reverse causality is present, then the model's recommendations will be invalid. Consider, for example, the service improvement training that is thought to have a positive impact on different SQ dimensions, such as R/A and EMP. Given the voluntary nature of this training, it is possible that employees who are predisposed to offer excellent service may also be predisposed to attend the voluntary training sessions. In this case, the causal relationship between training and SQ implied in our model may not hold, and the resulting recommendations will be invalid. Further investigation into the causal relationship between SQ and its drivers, such as, for example, between SQ and the different types of training, is necessary. Although the 3Ts framework, and information from internal and external customers through exploratory methods, as discussed above, can be helpful, the causal nature of such relationships can only be validated through carefully designed longitudinal research studies or strong prior theory studies (Blalock 1964).

Finally, it is important to emphasize that in the case where information on the prior distribution of the regression parameters is available, the method we present to obtain scenarios for the regression-based estimates cannot be followed. Instead, a Bayesian framework needs to be adopted, and the scenarios must be generated based on the posterior distribution of the regression coefficients. Other approaches that can account for uncertainty may also be worthwhile investigating.

6. Concluding Remarks

A major contribution of this paper is the development and preliminary testing of a service quality improvement approach driven by the linkage between process operational variables and customers' perceptions of SQ. Unlike other SQ improvement approaches found in the literature, it examines the different processes of the service delivery system at a microlevel, which allows specific modifications and improvements, in effect, to be engineered. In addition, the approach incorporates optimization models to identify a near-optimal operational characteristic mix, while taking into consideration the existence of uncertainty in the models' parameters. Thus, effectiveness measures such as customers' quality perceptions can be incorporated into the service manager's decision making. In summary, the approach presented here provides a useful diagnostic tool for SQ improvement for multistage service firms and, from a broader perspective, adds needed rigor to the study of service operations management.[1]

Appendix A Robust Optimization

The basic robust optimization formulation is presented by Mulvey et al. (1995). Consider the following optimization model:

(M3)

$$\text{Maximize } c^T x + d^T y. \tag{46}$$

$$\text{subject to } \quad Ax = b, \tag{47}$$

$$Bx + Cy = e, \tag{48}$$

$$x,\ y \geq 0. \tag{49}$$

where,

$x \in R^{n_1}$ a vector of decision variables whose value is not conditioned on the realization of any uncertain parameters.

$y \in R^{n_2}$ a vector of decision variables whose value is subject to adjustment once the uncertain parameters have been observed.

$d, B, C, e,$ coefficients of the optimization model whose values can be uncertain.

$A, b,$ coefficients of the optimization model whose values are fixed and free of noise.

Uncertainty can be captured by introducing a set of different scenarios $\Omega = \{1, 2, 3, \ldots, S\}$. A set $\{d_s, B_s, C_s, e_s\}$ is associated with each scenario $s \in \Omega$. Also associated with each scenario $s \in \Omega$ is the probability of the scenario $p_s (\Sigma_{s=1}^{S} p_s = 1)$. Mulvey et al. (1995) presented the following robust optimization formulation that can be solved to provide solutions, which remain close to the optimal for any scenario realization.

(M4)

$$\text{Maximize } \sigma(x, y_1, y_2, y_3, \ldots, y_s) - \omega\rho(z_1, z_2, z_3, \ldots, z_s) \tag{50}$$

$$\text{subject to } Ax = b, \tag{51}$$

$$B_s x + C_s y_s + z_s = e_s, \quad \text{for all } s \in \Omega, \tag{52}$$

$$x,\ y_s \geq 0, \quad \text{for all } s \in \Omega. \tag{53}$$

where,

$\{y_1, y_2, \ldots, y_s\}$ a set of control variables for each scenario $s \in \Omega$, ω a goal programming parameter, and $\{z_1, z_2, \ldots, z_s\}$ a set of error vectors that measure the infeasibility allowed in the control constraints under scenario s. In the existence of multiple scenarios, the objective function $c^T x + d^T y$ becomes a random variable. Different choices can be made for the function $\sigma(\cdot)$, one of them being the mean value, which is also the function used in stochastic linear programming. The function $\rho(\cdot)$ is the feasibility penalty function that can be used to penalize violations of the constraints under some scenarios. Thus, the goal programming parameter ω can be used to trade-off how close we are to optimality with how close we are to feasibility (see Mulvey et al. 1995 and Bai et al. 1997 for further discussion on robust optimization, the concepts of model robustness and solution robustness, and other choices of the functions σ and ρ) in order to provide a set of near optimal solutions that are "less sensitive" to the uncertainty, which may be observed in the model parameters.

Appendix B

This appendix demonstrates how **(M2)** can be generalized to the case of a multistage service system, using a specific choice for the objective function. Here, we introduce a set of scenarios $\Omega^i = \{1, 2, \ldots, S\}$, for each stage $i = 1, 2, \ldots, N$. We also introduce the probability of each scenario p_{is}, $\Sigma_s p_{is} = 1$, for each $i = 1, 2, \ldots, N$. Consider the following formulation, which maximizes SQ perceptions across service stages $i = 1, 2, \ldots, N$.

(M5) maximize

$$\sum_i \left(\sum_{s \in \Omega^i} p_{is}\, d_{is}^T y_{is} - \lambda \left[\sum_{s \in \Omega^i} z_{is}^T\, z_{is} + \sum_{s \in \Omega^i} \xi_{is}^T\, \xi_{is} \right] \right) \tag{54}$$

s. t.

$$A_{is} x_i^d + B_{is} x_{is}^c + z_{is} = y_{is} \quad \text{for all } s \in \Omega^i, \text{ and all } i = 1, 2, \ldots, N, \tag{55}$$

$$E_i x_i^d = a_i \quad \text{for all } i = 1, 2, \ldots, N, \tag{56}$$

$$C_s x_i^d + D_s x_{is}^c + \xi_{is} = c_{is} \quad \text{for all } s \in \Omega^i, \text{ and all } i = 1, 2, \ldots, N, \tag{57}$$

$$x_i^d,\ x_{is}^c,\ y_{is} \geq 0 \quad \text{for all } s \in \Omega^i, \text{ and all } i = 1, 2, \ldots, N. \tag{58}$$

where parameters are defined as in **(M2)**. Note that the main difference between **(M2)** and **(M5)** is that a distinction between control and design decision variables must be made for each stage $i = 1, 2, \ldots, N$. Furthermore, system constraints must also be identified and included in the model for each stage, which adds to the model's complexity. The first term of the objective function of **(M5)** maximizes the expected value of SQ, given the existence of multiple scenarios. The second term uses a quadratic penalty function to penalize violations of the constraints for the different realizations of the parameters. This is applicable to equality constraint problems where both positive and negative violations of the constraints are equally undesirable. The goal programming parameter λ is used to make trade-offs between solution and model robustness and determine a

[1]The authors are grateful to three anonymous reviewers, the senior editor, and the editor–in–chief, for their numerous and insightful suggestions, which significantly improved this manuscript. The authors would also like to thank Stavros A. Zenios and Hercules Vladimirou for valuable discussions during the initial stages of this work.

desirable solution, which will be immune to parameter uncertainty (see Mulvey et al. 1995).

In **(M5)** we use a simple weighted additive function to maximize SQ across stages. Note that, for simplicity, the importance of each stage in **(M5)** is incorporated in the set of importance weights d for each SQ dimension of each stage. The use of different functions—such as, for example, a function including an exponential term to capture such phenomena as "first impressions count" (Maister 1985)—could also be investigated.

Appendix C

Service Quality Measurement Instrument: All items measured on a 7-point scale: 1 = *poor*, 7 = *excellent*.

The Financial Screening Area

1. The employees were neatly dressed.
2. The financial screening area was clean.
3. Signs and decoration in the financial screening area were appropriate.
4. You did not have to wait to see the employee.
5. The time it took to complete what had to be done at the financial area was reasonable.
6. The employee was not willing to help you.
7. The employee gave you individual and personal attention.
8. The employee was not sensitive to your individual problems.
9. The employee had your best interest at heart.
10. The employee explained well what he/she was doing.
11. The employee was not courteous.
12. The employee showed sincere interest in answering your questions.
13. The employee was competent.
14. The employee instilled confidence in you.
15. Did you have to wait to see the financial screening employee? If yes, approximately how many minutes?

The Examination Area

Your health care provider was (you can check more than one box):
☐ a physician ☐ a physician assistant ☐ a social worker ☐ a nurse ☐ I don't know

1. The provider was neatly dressed.
2. The examination area was clean.
3. Signs and decoration in the examination area were appropriate.
4. You did not have to wait to see the provider.
5. The time it took to complete the examination was reasonable.
6. The provider was not willing to help you.
7. The provider gave you individual and personal attention.
8. The provider was not sensitive to your individual problems.
9. The provider had your best interest at heart.
10. The provider explained well what he/she was doing.
11. The provider was not courteous.
12. The provider showed sincere interest in answering your questions.
13. The provider was competent.
14. The provider instilled confidence in you.
15. Did you have to wait to see the health care provider? If yes, approximately how many minutes?

Note:
Questionnaire items 1–3, 4–6, 7–9, 10–12, 13, and 14 correspond to the dimensions of tangibles, responsiveness, empathy, assurance and reliability, respectively, as proposed by Parasuraman et al. (1988).
An overall quality statement (QUAL), capturing the level of overall perceived quality at each stage, was also included for each stage.

Appendix D. Variable Definition and Descriptive Statistics for the Examination Area

	Variable name	Definition	Mean	SD
Task	DURATION	Stage Incident duration (in minutes).	10.1	2.8
	WAIT	Waiting time (in minutes) before patient was seen by provider.	52.2	9.4
	NURSE	Number of nurses at the time of the incident.	4.5	0.7
	PA	Number of physician assistants present at the time of the incident.	3	0.1
	NP	Number of nurse practitioners present at the time of the incident.	3	0.2
	MD	Number of physicians present at the time of the incident.	3.2	0.8
	k	Number of health care providers in the work unit area present at the time of the incident, i.e., in the examination area; k = MD + PA + NP + NURSE.	13.7	1.3
	PROV	A discrete variable indicating the type of provider (applicable in the exam area).		
Treatment	SITrain	The amount of Service Training the provider received during the last year (in days).	5.73	1.8
	CDTrain	The amount of Cultural Diversity Training the provider received during the last year (in days).	3.72	1.2
Tangible	BATHtime	The amount of time (in minutes) elapsed between the beginning of the waiting time and the last time the bathroom was cleaned.	23.9	10.4
	MOPtime	The amount of time (in minutes) elapsed between the beginning of the waiting time and the last cleaning time.	90.5	9.4
	MOP	The number of times the waiting area was mopped during the day.	2.3	0.1
	BATH	The number of times the bathroom was cleaned during the day.	2.1	0.3
Other provider or patient characteristics	AGE	A continuous variable indicating the age of the patient.	34	8.2

Appendix D. (Continued)

Variable name	Definition	Mean	SD
EDUC	A discrete variable (1–7) indicating patient's education.	2.3	0.4
XVISIT	A discrete variable (1–6) indicating the frequency of visits during the last two months at the clinic.	1.8	0.3
HEALTH	A discrete variable (1–7) indicating the customer's overall health during the last four days.	4.6	1.1
PROF	The amount of professional training of the health care provider, measured as the number of years elapsed since completion of medical or nursing school.	11.4	2.9
OTHERVISIT	A 0 or 1 variable indicating whether the patient has visited other clinics for his/her treatment.		
MARRY	A discrete variable (1–4) indicating the patient's marital status.		

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The consulting Senior Editor for this manuscript was Aleda Roth. This manuscript was received on May 25, 1999, and was with the authors for 141 days for 3 revisions. The average review cycle time was 48 days.