Overbooking Increases Patient Access at East Carolina University’s Student Health Services Clinic

John Kros, Scott Dellana, David West
Department of Marketing and Supply Chain Management, College of Business, East Carolina University, Greenville, North Carolina 27858 {kros@ecu.edu, dellanas@ecu.edu, westd@ecu.edu}

The health-care clinic presented in this study experienced significant numbers of patients who failed to arrive for their scheduled appointments (no-shows). The cost of reducing patient access at this clinic because of no-shows is estimated to exceed $400,000 annually. An interdisciplinary quality-improvement team developed a novel health-care overbooking model that includes the effects of employee burnout. This model estimates the nonlinear nature of the costs associated with medical-provider burnout caused by overbooked appointments that exceed clinic capacity. Several key East Carolina University clinical staff members had been skeptical about the value of overbooking. The model was instrumental in convincing them that implementing an overbooking process would benefit patients and the organization. The clinic, which subsequently implemented such a process, attributes a savings of $95,000 per semester to the initiative.

Keywords: decision analysis; health care; production scheduling; simulation; probability: applications; stochastic model applications.

History: This paper was refereed. Published online in Articles in Advance.

Introduction

East Carolina University (ECU), which is located in Greenville, North Carolina, has an enrollment of approximately 23,000 students, and has 5,400 faculty and staff. ECU is a public university and a member of the North Carolina university system. The ECU Student Health Service (SHS), which is the health clinic for the ECU campus population, provides health-care services and wellness education to enrolled students. On any given day in a typical semester, 5 to 10 providers are available to diagnose and treat campus patients. These providers typically include both medical doctors and physician assistants. The provider staff is augmented by nutritionists, nurses, pharmacists, an x-ray technologist, and support staff, and delivers a broad range of health-care services to the ECU community. The 16,000-square-foot SHS facility, which consists of 25 exam rooms and three observation beds, is supported by pharmacy, laboratory, and radiology resources.

Patient volume for the ECU SHS consists almost entirely of appointments scheduled in advance for nonurgent health-care needs. Each patient is typically scheduled with a particular provider based on the patient’s specific needs and the provider’s expertise. Only selected providers are authorized to perform surgical procedures; one provider sees only women. Two providers specialize in sports medicine. On any given day, they work almost entirely with athletes, leaving three to seven providers to see only regular patients. (These remaining providers are also the only ones eligible to be overbooked.) Thus, on average, the equivalent of six providers is available to see regular patients. In a recent academic year, 35,050 appointments were scheduled. Approximately 3,800 (10.8 percent) of these appointments were no-shows—patients who failed to arrive for their scheduled appointments. The ECU SHS no-show problem is not unique. Various studies report that no-show rates for private clinics range between 2 and 26 percent (Smith and Yawn 1994, Barron 1980, Oppenheim et al. 1979). Deyo and Inui (1980) report no-show rates in general adult and pediatric clinics that range between 15 and 30 percent. Clinic no-show rates as high as 50 percent have also been reported (Hixon et al. 1999). The cost of no-shows in a health-care clinic has been discussed...
extensively in the literature (Macharia et al. 1992, Cayirli and Veral 2003). No-shows disrupt schedules and idle scarce health-care providers. Missed appointments also make it more difficult for other patients needing care to receive timely service when clinic schedules are full (Bean and Talaga 1995).

The SHS operates as a not-for-profit organization; it receives no revenue for patient visits. Its costs, including facility and staff, are allocated in the university budgeting process. At the time of this study, the SHS calculated its average cost per patient visit to be $137 and reported operating at 100 percent capacity during 83 percent of the scheduled days. Because most health-care providers value patient access more than the costs of providing services, a conservative estimate of the loss of patient access associated with no-shows is $400,000 (3,800 no-shows times $137 per appointment times 0.83 of days fully scheduled).

The ECU SHS has attempted to reduce the no-show rate by using patient reminder and prompting systems and short lead-time appointments. Most patients are seen within 24 hours of making an appointment, thereby substantially reducing the chance that a patient gets better prior to the appointment. Bigby et al. (1983) report that a reminder system reduced no-shows from 24 to 14 percent. Nonetheless, moderate to high no-show rates are likely to persist even in clinical settings where measures are taken to reduce them.

The authors joined with six members of the SHS staff to form a quality-improvement (QI) team to study the no-show problem and to analyze an overbooking option (i.e., booking more than one patient in an appointment time slot). The QI team members included the authors, the SHS director, the senior staff physician, the systems administrator, the medical records manager, the QI coordinator, and the nurse manager. The SHS director communicated to the SHS staff that some degree of overbooking appointments could offset the adverse effects of no-shows. Major benefits of this overbooking strategy were recognized as increased utilization of the health-care providers and increased access to SHS care (more patients could be seen and patients could be scheduled sooner). Organizational costs occur for those days with overscheduled patients (i.e., when the number of patients exceeds the number of scheduled appointments available), including longer waits by patients and pressures on health-care providers who must extend their working hours. The director reported that SHS health-care providers exhibited skepticism and outright resistance to the overbooking proposal because of possible negative effects. One skeptic was a provider on the QI team. This resistance was expected; studies report that clinical staff personnel often resist scheduling changes that place additional pressures on them (Bennett and Worthington 1998, Huang and Lee 1996). Because health-care providers are individuals with a high degree of expertise, they command significant authority in service organizations; therefore, decision making in clinical settings involves high political stakes. The ECU SHS staff’s initial resistance to overbooking appointments is natural, considering society’s negative impressions of overbooking and reports of possible detrimental effects from overbooking (Walter 1973, Groitein 1990). Clinical staff also generally resist any changes that place additional pressure on them to improve scheduling systems (Bennett and Worthington 1998, O’Keefe 1985, Huang and Lee 1996). To address these concerns, the SHS director charged the QI team with performing an analytic study of the potential costs and benefits of overbooking the SHS clinic appointment schedule. The objective of the QI team was to investigate the feasibility of overbooking, with the ultimate goal of achieving organizational acceptance, especially from the physicians and nurses who would experience the greatest impact from overbooking.

**Services Overbooking Literature**

The concept of overbooking has been well developed in many service industries, particularly the airline industry. The reader is referred to Rothstein (1971) and McGill and van Ryzin (1999) for excellent reviews of the theory and application of overbooking. Airlines have historically experienced domestic-flight no-show rates that exceed 15 percent (Smith et al. 1992). The US airline industry has gained significant financial benefits from overbooking (Alstrup 1989, Curry 1990, Davis 1994). Although these studies do not relate directly to health care, they infer potential benefits of overbooking in clinical settings.

The health-care–related literature reports several overbooking studies. Early work by Shonick and Klein (1977) propose using simple estimated conditional
probabilities of patient appointment-breaking as a smart approach to overbooking. The sum of probabilities for patients scheduled in a day was taken as the expected number of kept appointments to fill daily capacity. However, the effects on waiting times and costs were not considered and appointment lead time was not discussed. Vissers (1979) presents research on the relationship between patient prepunctuality and both patient waiting time and provider idle time in the health-care industry by using simulation models. This research compared overbooking appointments evenly throughout the clinic session with shortening the appointment interval, and concluded that shortening the appointment interval gives a better balance of idle and waiting times. The study did not consider costs, discuss appointment lead time, or report the simulation logic and details. However, based on this research some health-care facilities implemented “naïve overbooking models” to address high no-show rates and cancellations (Kim and Giachetti 2006). The naïve model is an overbooking policy based on the average no-show rate. Overall, naïve overbooking in cases with high no-show rates is not optimal. Statistical overbooking models, however, can greatly improve system performance (Pierskalla and Brailer 1994, Kim and Giachetti 2006).

Rohleder and Klassen (2002) follow with a simulation to study a rolling-horizon appointment schedule approach designed to bring modeling closer to the realities of clinic scheduling when long lead times are involved. The research was based on simple interviews at two clinics. Call arrival times were exponentially distributed, and a 5 percent no-show rate was assumed. Six demand patterns and six overloading scenarios were studied. The primary measure used was the minimum combined server idle time and client waiting time. The study reported benefits to the organization with either overtime or double booking of appointments (but with significantly increased patient waiting time). This research did not consider the costs of overbooking. Kim and Giachetti (2006) were the first to propose a stochastic mathematical optimization model (SMOM) that demonstrates the profit associated with an overbooking policy in a for-profit health-care clinic. The study considers no-shows and compares SMOM to no overbooking and naïve statistical overbooking (mean no-shows minus mean walk-ins). It did not discuss appointment lead time issues. An upper limit was placed on the allowable number of overscheduled patients. Overtime and waiting-time penalty costs, derived from discussions with clinic personnel, were assumed to be linear. The researchers define financial benefits for the organization and potential benefits for the patient, including reduced waiting times for appointments and increased continuity of care. They do, however, caution that average patient waiting time at a clinic will likely increase with overbooking and suggest possible actions to minimize this effect.

Most recently, LaGanga and Lawrence (2007) extend health-care overbooking research by proposing a model for estimating the financial value from overbooking in a clinic setting. They hold service time constant while varying the no-show rate. However, they do not discuss appointment lead time issues. Waiting time and overtime in the model (which were shown to increase with the no-show rate) incur a marginal “cost” per unit of time with a linear function. They ran simulations to test various clinic settings, with parameter values developed from consultation with administrators at a mental health clinic, but do not report clinic implementation and follow-up to support the model recommendations.

Economics of Clinic Overbooking
A key distinction between overbooking models for fixed-capacity systems (e.g., airlines) and adjustable-capacity health-care systems is the nature of the “bumping” process and its impact on service providers. When the number of customers exceeds the capacity, fixed-capacity systems use a process to determine which customers will be denied service (i.e., bumped). A major cost of overbooking in these systems is the service-recovery effort to make acceptable alternative arrangements for the bumped customers. The airlines use an auction system that includes frequent flyer awards, alternative flight arrangements, hotels, meals, etc. By contrast, health-care system capacity can often be expanded so that all regularly scheduled and overbooked patients are served; no one is “bumped.” The costs of overscheduling for the health-care system in our study are not primarily the costs of accommodating customers, but rather the burnout cost imposed on service providers who see more patients and must extend their workday
beyond the normal clinic-session hours. Burnout pressures can also result from the shorter durations that occur when patients are “worked into” the normal operating hours. This is referred to as quantitative overload and results from an individual’s perceptions that the workday cannot be extended and that the staff will be overloaded with patients (Cordes and Dougherty 1993). Employee burnout is a unique type of stress syndrome characterized by emotional exhaustion, depersonalization, and diminished personal accomplishment (Cordes and Dougherty 1993). Empirical evidence shows that burnout has significant negative ramifications and substantial costs for both organizations and individuals. These effects are particularly acute in work environments that are characterized by direct, frequent, and intense interactions with customers, such as health care. Burnout creates absenteeism, reduced productivity, and other human considerations (Cordes and Dougherty 1993). Health-care providers might eventually resign, causing the organization to incur substantial replacement costs. According to research, the cost of replacing a primary care physician approaches three times her annual salary (Buchbinder et al. 1999).

The contribution of our research is a novel method of modeling the costs of overbooking in a health-care application. Our model differs from conventional overbooking algorithms that treat the costs of overbooking as a constant cost of overtime per overscheduled patient. In this research, overbooking costs are a nonlinear function of the overbooking rate derived from earlier research on employee burnout. We believe this is the first time an economic burnout model has been used in the value function of a health-care overbooking model. In addition, the clinic in our study has a short schedule lead time: most of its patients are seen within 24 hours of making an appointment. Finally, the overbooking recommendations are implemented in a real clinic over a significant period and the resulting benefits are reported.

The ECU SHS Overbooking Model Development

At the QI team’s kickoff meeting, the nurse manager provided operational information and data for the development of a management science operational model. The conceptual model (Figure 1) consists of prediction models for the number of patient appointments and the proportion of no-shows, an aggregate capacity model to meet varying monthly demands, an appointment overbooking model, which includes a clinic-scheduling algorithm, and a burnout model to reflect the organizational costs of overscheduled patients. We discuss each component of the conceptual model in the following subsections.

Predictive Models for Total Clinic Appointments and No-Shows

Figure 2 portrays monthly time-series data of patient appointments to the SHS for a recent four- to five-year period. The monthly variation in visits tracks the university academic calendar, which defines the number of days the student population is present on campus, and key periods of health concerns, such as flu epidemics. The prediction model that best fits the SHS monthly visit data is a seasonal dummy model with an $R^2$ of 0.82 and a mean absolute percent error (MAPE) of 3.48 percent. Tests for trend components in the time series were not significant; Dickey-Fuller seasonal and unit root tests (Dickey and Fuller 1979) confirmed that the time series is stationary. White noise tests on the model residuals suggest no autocorrelation, although a few lags were close to significance. The patient appointment time series was also analyzed for day-of-week variability. Demand on Friday with an index of 0.79 reflects lower demand than on the Monday through Thursday period, which varies from 1.03 to 1.08. The model results developed here are used in the overbooking model as estimates for the appointment demand-distribution parameters.

Figure 3 shows a time series of the monthly proportion of total clinical appointments that were no-shows ($P$). This proportion varies from a low of approximately 0.06 to a high in excess of 0.12, and averages 0.096. The prediction model fit to this time series is a seasonal exponential smoothing model with an $R^2$ of 0.60 and a MAPE of 11.5 percent. The prediction equation is

$$\hat{P}_t = L_t + S_{t-p+k}, \quad (1)$$

with smoothing coefficients calculated as follows:

$$L_t = \alpha (P_t - S_{t-p}) + (1 - \alpha) L_{t-1}, \quad (2)$$

$$S_t = \delta (P_t - L_t) + (1 - \delta) S_{t-p}, \quad (3)$$
The relatively high value of MAPE results from a large random component in this time series. Again, unit root tests and white noise tests suggest that the residuals are stationary and contain no significant information. An analysis of the daily variation of $P$ shows minor variations in the Monday through Thursday period; no-shows tend to be fewer on Fridays, with an index of 0.83.

A correlation between appointments and $P$ indicate that the two time series are essentially independent, with a small negative correlation of $-0.075$. Therefore, we can determine the number of no-shows as $P$ multiplied by total clinical appointments.

**Clinic Capacity Scheduling**

The predicted levels of clinic appointments vary substantially from a high of 4,361 appointments in September to a low of 1,234 in July, a range of 3.5:1. The data are contained in Table 1. To accommodate this extreme variation, the SHS uses a flexible service-delivery system employing a chase strategy aggregate plan that adjusts the provider workforce level to the monthly clinic demand level. This strategy creates high provider utilization rates throughout the year and creates an environment in which the decision to overbook the clinic will have economic implications each month.

The flexibility of provider supply is accomplished with employment agreements that focus on flexible work hours and seasonal terms of employment. The SHS has a dedicated group of medical providers who place high value on quality-of-life issues. These employees value both a standard workweek and lighter workloads during the summer months. This is an ideal match with the SHS needs but presents one significant issue: higher levels of appointment overbooking will increase job stress and extend working hours in an unpredictable way. Under such conditions, employee burnout can lower morale and increase employee turnover.

**Appointment Overbooking Model and Scheduling Algorithm**

A value function is useful in guiding scheduling policy for not-for-profit organizations that lack explicit revenue accounting (Metters and Vargas 1999, LaGanga and Lawrence 2007). LaGanga and Lawrence claim that they developed the first overbooking utility

![Diagram](image-url)
model for a health-care clinic. We use Lawrance’s general concept of utility for patient access and patient waiting time, but replace their use of a constant marginal cost of overtime with the Gompertz function to model the cost of provider burnout.

The appointment model for the SHS clinic consists of multiple providers who serve a dedicated set of scheduled patients with specific appointments times. Over time, the SHS has adopted specific-duration appointment times that best suit its clinic setting. Each patient is seen for a fixed and constant duration of time $D_i$ ($D_1 = 15$ minutes, $D_2 = 30$ minutes). The actual service times for the SHS clinic exhibit little variability because of the routine and standardized nature of the services offered. For example, 15-minute intervals are scheduled for abrasions, allergies, asthma, boils, cramps, earaches, flu, etc., while 30-minute intervals are scheduled for insomnia, back pain, medicine evaluations, migraines, etc. More-complicated cases are referred to local urgent-care clinics or the emergency room of a nearby hospital. These intervals were considered the practical minimum for the SHS.

The SHS schedules two clinical sessions, one morning session and one afternoon session, separated by a one-hour lunch break. It has a finite capacity defined as $N = \text{maximum capacity of clinic in appointments per day}$. A typical day at the SHS consists of a maximum of 168 appointments, of which one-third are 30 minutes in duration and two-thirds are 15 minutes in duration. The average appointment duration is 18.75 minutes, a weighted average of 30-minute and 15-minute appointments.

The overbooking model recognizes three system-capacity states. On days where the number of appointments booked by the clinic is less than the clinic capacity, no overbooking is necessary. When the number of appointments exceeds the clinic capacity, there are two possible states: First, when the number of no-shows exceeds the number of overbooked appointments, patient access is increased at no additional
organizational costs. Second, when the number of overbooked appointments exceeds the number of no-shows, overscheduled appointments are generated. This creates pressure on the service providers and causes the patient waiting time to increase (LaGanga and Lawrence 2007). The value function must measure the marginal economics of three factors: (1) the value of patient access, (2) the cost of patient waiting time, and (3) the provider burnout costs.

Patient access value, \( U_{\pi} = \pi \times MIA \), is the benefit of the treatment of one additional patient, \( \pi \) (in dollars per patient served), multiplied by the marginal increase in patients treated (\( MIA \)) because of a specific overbooking policy. Overbooking increases the total clinical appointments and patient access. We use a value of $137 for \( \pi \); this is the calculated cost per patient who is treated by the SHS.

All patients will experience some waiting time because of the stochastic nature of the service-delivery system at the SHS. Historically, waiting times have averaged approximately 10 minutes. The value function measures the marginal increase in waiting times, \( V_{PW} = \omega \times PW \), caused by a specific overbooking policy. Patient waiting value, \( V_{PW} \), is the marginal cost (an opportunity cost) multiplied by an estimate of additional patient waiting time, \( PW \). \( PW \) is the cumulative waiting time for all patients and is defined as \( D \).

A closed-form solution for patient waiting time is not attainable. Therefore, we estimated the cumulative waiting time by enumerating the possible patient waiting times that occur because of overscheduling patients. We then used these data to create a lookup table that the overbooking model draws from depending on the number of overscheduled patients. When there are no overscheduled patients, \( PW = 0 \); when the number of overscheduled patients is greater than zero, we draw a value of waiting time, \( PW \), from the lookup table and use it to calculate the value of

Figure 3: The graph depicts the proportion of patient visits that are no-shows for July 1999 to December 2004. The proportion averages approximately 9.6 percent.
Table 1: The data show predicted student demand for appointments and no-show prediction proportions by month.

<table>
<thead>
<tr>
<th>Month</th>
<th>Predicted demand</th>
<th>Proportion no-show</th>
</tr>
</thead>
<tbody>
<tr>
<td>July</td>
<td>1,234</td>
<td>0.0994</td>
</tr>
<tr>
<td>August</td>
<td>2,248</td>
<td>0.0784</td>
</tr>
<tr>
<td>September</td>
<td>4,361</td>
<td>0.0876</td>
</tr>
<tr>
<td>October</td>
<td>4,271</td>
<td>0.1151</td>
</tr>
<tr>
<td>November</td>
<td>4,103</td>
<td>0.1125</td>
</tr>
<tr>
<td>December</td>
<td>2,475</td>
<td>0.1209</td>
</tr>
<tr>
<td>January</td>
<td>3,363</td>
<td>0.0826</td>
</tr>
<tr>
<td>February</td>
<td>4,136</td>
<td>0.1077</td>
</tr>
<tr>
<td>March</td>
<td>3,435</td>
<td>0.1135</td>
</tr>
<tr>
<td>April</td>
<td>3,803</td>
<td>0.1209</td>
</tr>
<tr>
<td>May</td>
<td>1,818</td>
<td>0.1214</td>
</tr>
<tr>
<td>June</td>
<td>1,256</td>
<td>0.1077</td>
</tr>
</tbody>
</table>

Table 2: The data show cumulative patient waiting time per number of overscheduled patients.

<table>
<thead>
<tr>
<th>Overscheduled patients</th>
<th>Cumulative waiting time/min</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>87.50</td>
</tr>
<tr>
<td>2</td>
<td>209.375</td>
</tr>
<tr>
<td>3</td>
<td>366.625</td>
</tr>
<tr>
<td>4</td>
<td>556.250</td>
</tr>
<tr>
<td>5</td>
<td>781.250</td>
</tr>
<tr>
<td>6</td>
<td>1,046.625</td>
</tr>
<tr>
<td>7</td>
<td>1,334.575</td>
</tr>
<tr>
<td>8</td>
<td>1,662.500</td>
</tr>
<tr>
<td>9</td>
<td>2,025.000</td>
</tr>
<tr>
<td>10</td>
<td>2,421.875</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>37</td>
<td>34,146.875</td>
</tr>
</tbody>
</table>

Patient waiting. Table 2 shows an abbreviated version of the lookup table. The value of $\omega$ is set at $25 per hour for this research, reflecting the opportunity cost of student time under conditions in which waits are relatively short and the student does not have a serious health problem.

Provider burnout value, $V_{PB}$, is the marginal cost of the psychological pressures on medical providers from overscheduled patients and is defined as $V_{PB} = \rho \times PB$. The parameter $\rho$ is an estimated constant cost per overscheduled patient calculated from the typical overtime cost of a medical crew (LaGanga and Lawrence 2007). $\rho$ is then scaled by a nonlinear logistic function that estimates the provider burnout costs as a function of the number of overscheduled patients ($OS$); $PB = OS \times LF$. The burnout pressures are modeled according to a logistic function, $LF = A \times e^{-e^{-(OS + \beta) \times \rho}}$, fitted from qualitative information provided by the SHS staff. Equation (4) contains the provider burnout value:

$$U_{PB} = \rho \times OS \times A \times e^{-e^{-(OS + \beta) \times \rho}}.$$  \hspace{1cm} (4)

Total value from overbooking is then represented as patient access value minus patient waiting value less accrued provider burnout.

$$V_T = V_{PA} - V_{PW} - V_{PB}$$ \hspace{1cm} (5)

$$= \pi \times MIA - \omega \times PW - \rho \times PB,$$ \hspace{1cm} (6)

where $MIA = OS \times NIA$, and $NIA$ is the net increase in patients serviced because of the overbooking policy.

$$PW = \begin{cases} 0 & \text{OS} = 0, \\ \text{Value from lookup table based on } OS & \text{OS} \geq 1, \end{cases}$$ \hspace{1cm} (7)

and $PB = OS \times LF$, all of which are functions of $OS$. The optimal overbooking policy is then found from

$$\text{Max } V_T(OR) = \max \pi \times MIA - \omega \times PW - \rho \times OS \times A \times e^{-e^{-(OS + \beta) \times \rho}}.$$ \hspace{1cm} (8)

The appendix provides details of the overbooking algorithm.

Provider Burnout Modeling

Li et al. (2000) model the effects of overtime work on costs and quality using system dynamic models developed by Forrester and Senge (1980). The authors consider dynamic interactions among employee burnout, employee attrition, hiring and training of new employees, schedule pressures, overtime, fatigue, motivation, quality, and rework. The functional form for the cost function reveals a logistic shape formally proposed by Gompertz in 1825 (Smith and Keyfitz 1977); minor cost increases for small levels of overtime are followed by an exponential increase that eventually reaches an asymptotic maximum.

The Gompertz form for modeling of burnout costs as a function of overscheduled patients is validated by
the clinic’s economics. The medical providers are professional employees who are not paid overtime; they voluntarily serve a few overscheduled patients. Consequently, the function for burnout should start at the origin and reflect negligible costs for small levels of overscheduled patients. The medical provider’s value for quality-of-life issues will result in exponentially increasing costs in the regime in which the number of overscheduled patients is large enough to create significant work pressures and opportunities for medical errors. Finally, the function should reach an asymptotic maximum at a level of overscheduled patients that results in frequent attrition and replacement of medical providers. The general Gompertz curve is expressed as follows:

\[ Y_x = A \cdot e^{-c \cdot (b_0 + b_1 \cdot e^{-b_2 x})}, \]  

(9)

where the variables are defined as follows:

- \( Y_x \): burnout associated with overscheduled patients.
- \( x \): number of overscheduled patients.
- \( A \): upper asymptotic weight as the number of overscheduled patients \( x \) approaches the upper limit of provider burnout.
- \( b_0 \): slope of the growth curve when \( x = 0 \) (the initial specification of growth rate).
- \( b_1 \): rate of exponential decay of the initial specification of the growth rate \( b_2 \), which measures the rate of decline in the growth rate.

The fitting of parameters for the Gompertz function is necessarily based on qualitative information provided by the SHS staff to identify the location of two inflection points. The SHS staff believed that provider burnout would begin at a level of three overscheduled patients (about one extra hour of clinic operation). Burnout costs transition from negligible to exponential growth at this point. The staff stated that the second inflection point occurred as the number of overscheduled patients increased to 10, or after about three hours of clinic operation. At this level, provider burnout pressures would be intolerable and serious repercussions would ensue, including absenteeism, medical errors, and employee turnover.

The upper limit of provider burnout, \( A \), was set to 3. This upper limit is the relative cost associated with replacing a physician (Buchbinder et al. 1999). An argument can be made that this ceiling is conservative because it does not include the substantial costs of medical errors. To counter this concern, we also examine burnout using a ceiling of 2 and 4 in a sensitivity analysis. The appendix shows the algebraic derivation of the Gompertz curve equation parameters. Figure 4 displays a graph of the function.

**Overbooking Model Results, Sensitivity, and SHS Staff Presentation**

Within 10 months of the kickoff meeting, the team completed the overbooking model, which served as a decision aid to quantify the benefits and consequences of different levels of overbooking the SHS schedule. Shortly thereafter, the QI team presented to the SHS staff the consequences of overbooking the clinic schedule by levels of 0, 5, 10, and 15 percent. The primary focus of the presentation was on the graphical display of pertinent performance measurements produced by the model. The demonstrated benefits of overbooking communicated at the meeting were instrumental in overcoming staff resistance to overbooking the SHS clinical appointments.

The presentation included an overview of the overbooking model and the concept that the results were averages of 100,000 iterations. Performance measurements included in the model were the number of overscheduled patients and the value generated by overbooking.

Table 3 displays the associated statistics and value calculations for the SHS overbooking model. These results are based on an upper threshold for the
provider-burnout scaling function of three and a $p$ of $75$ per overscheduled patient. The net increase in patient access because of overbooking at the SHS ranged from 2.8 patients with 2 percent overbooking to approximately 22.3 patients at 22 percent overbooking. For example, there is an average net increase of approximately 6.2 patients from no overbooking to 5 percent, an increase of approximately 5.25 patients from 5 to 10 percent, and an increase of approximately 5.2 patients from 10 to 15 percent. The statistic “mean overscheduled patients” summarizes instances in which realized demand exceeds scheduled capacity. In an airline model, we would refer to this as “number bumped,” because capacity is immutable and customers must be denied service. For example, the expected number of overscheduled patients per day predicted by the model is 0.02 for 5 percent overbooking, 0.49 for 10 percent overbooking, and 3.19 for 15 percent overbooking. Average total appointments through the SHS rose from 138 with no overbooking to 144 with 5 percent overbooking, 149 with 10 percent overbooking, and 154 with 15 percent overbooking.

It is apparent that the value of patient access continually increases as the rate of overbooking increases. Higher rates of overbooking also lead to higher costs for waiting time and provider burnout. For example, over the range of overbooking policies from 2 percent up to 22 percent, the value associated with patient waiting costs increases from approximately zero to $1,890$. Figure 5 displays the total value for the 10 overbooking strategies, and shows that an overbooking level of 13 percent is the most favorable for the organization.

To provide a perspective of the sensitivity of this conclusion to the parameters used, the coefficient, $\pi$, is fixed, while $\rho$, $\omega$, and the upper level of the Gompertz $S$ curve are allowed to vary. The values of $\rho$ used in the sensitivity analysis are $50$, $75$, and $100$, the values of $\omega$ are $12.5$, $25$, and $37$, respectively, while the upper levels of the Gompertz $S$ curve values are 2, 3, and 4, respectively. Table 4 displays the sensitivity analysis for total value associated with various levels of overbooking.

At all levels of $\rho$, $\omega$, and the upper level of the Gompertz $S$ curve, the maximum value occurs between overbooking levels of 10 and 15 percent. High levels of overbooking (e.g., 15 percent) are supported under the conditions of lower waiting costs, lower provider burnout thresholds, and an upper provider burnout threshold of 2 or, at times, 3. Generally speaking, as these costs start to rise the more favorable overbooking level tends towards 10 percent.

Table 3: The data show summary statistics for the overbooking model: Upper Gompertz boundary $A = 3$ and $p = 75$.

<table>
<thead>
<tr>
<th>Overbooking policy</th>
<th>2%</th>
<th>5%</th>
<th>7%</th>
<th>10%</th>
<th>13%</th>
<th>15%</th>
<th>18%</th>
<th>20%</th>
<th>22%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean overscheduled patients</td>
<td>0.00</td>
<td>0.02</td>
<td>0.09</td>
<td>0.49</td>
<td>1.64</td>
<td>3.19</td>
<td>5.59</td>
<td>7.09</td>
<td>8.56</td>
</tr>
<tr>
<td>SE</td>
<td>0.15</td>
<td>0.40</td>
<td>0.55</td>
<td>0.81</td>
<td>1.13</td>
<td>1.42</td>
<td>1.79</td>
<td>2.04</td>
<td>2.30</td>
</tr>
<tr>
<td>Mean net increase in patient access</td>
<td>2.82</td>
<td>6.20</td>
<td>8.16</td>
<td>11.30</td>
<td>14.29</td>
<td>16.55</td>
<td>19.24</td>
<td>20.78</td>
<td>22.25</td>
</tr>
<tr>
<td>SE</td>
<td>1.80</td>
<td>4.06</td>
<td>5.40</td>
<td>10.39</td>
<td>10.46</td>
<td>10.48</td>
<td>7.50</td>
<td>9.16</td>
<td>9.97</td>
</tr>
<tr>
<td>Mean total actual appointments</td>
<td>140.26</td>
<td>143.65</td>
<td>145.61</td>
<td>148.75</td>
<td>151.73</td>
<td>154.00</td>
<td>156.69</td>
<td>158.22</td>
<td>159.70</td>
</tr>
<tr>
<td>SE</td>
<td>4.11</td>
<td>4.51</td>
<td>4.74</td>
<td>5.15</td>
<td>5.56</td>
<td>5.89</td>
<td>6.31</td>
<td>6.56</td>
<td>6.82</td>
</tr>
<tr>
<td>$U_{na}$ ($$)</td>
<td>388.44</td>
<td>856.12</td>
<td>1,126.60</td>
<td>1,560.13</td>
<td>1,971.41</td>
<td>2,284.06</td>
<td>2,654.93</td>
<td>2,866.67</td>
<td>3,070.01</td>
</tr>
<tr>
<td>$U_{oa}$ ($$)</td>
<td>(0.04) (1.14) (4.82) (32.84) (134.99) (314.18) (702.88) (1,032.88) (1,432.75)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$U_{wa}$ ($$)</td>
<td>(0.04) (1.96) (9.12) (67.67) (283.00) (620.60) (1,190.03) (1,551.58) (1,899.11)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$U_{r}$ ($$)</td>
<td>388.36</td>
<td>853.02</td>
<td>1,112.66</td>
<td>1,459.62</td>
<td>1,553.42</td>
<td>1,349.28</td>
<td>762.03</td>
<td>282.21</td>
<td>(261.85)</td>
</tr>
</tbody>
</table>
no-shows, causing low realized demand. There are no overscheduled patients at the 5 percent overbooking level on 95 percent of the operating days. During the remainder of the days, overscheduled patients could vary from one to a maximum of eight, which would occur approximately two days a month. The 10 percent overbooking level has no overscheduled patients 85 percent of the time; the number overscheduled will vary from 1 to 16 during the remainder of the days. Finally, the 15 percent overbooking level has no overscheduled appointments 50 percent of the time and a maximum of 25 overscheduled appointments. It was evident during the discussions that the SHS staff felt that the 5 percent overbooking policy would be easily managed. Discussion ensued about how the staff could minimize the consequences of the levels of overscheduled patients that the model predicted.

Implementation of Overbooking at the ECU SHS

The consensus of the group at the conclusion of the meeting was that overbooking should be implemented. The SHS staff members, and specifically the medical providers, believed that the organization should start by overbooking two slots per day (between 5 and 10 percent) for one semester, and increase the overbooking rate as they gained confidence and skill. They recognized that higher overbooking levels had more value to the organization. The consequences for the few patients who would be overscheduled could be minimized; the cost savings resulting from the more efficient use of staff resources was significant. Selected SHS staff members subsequently experimented with the model to gain further acceptance and assurance prior to the actual implementation. Satisfied, they then proceeded with the planned implementation.

The ECU SHS staff implemented a policy of two double-booked time slots per eligible provider per day during the semester following the model presentation meeting; the staff viewed this as a way to increase health-care access without having to ask the State of North Carolina for an increase in staffing levels and facility space. Overbooking was done selectively, based on the time of day. In the morning clinical session, the 8:45–10:45 AM period was
usually targeted. In the afternoon clinical session, overbooking was considered for the 1:30–3:45 pm period. If needed, one morning and one afternoon appointment were double-booked for each health-care provider working a full schedule. This policy spread out the potential work imbalances of overbooking throughout the day. In addition, the scheduler did not arbitrarily overbook time slots but instead examined each appointment for type and content to assess which were the best candidates to overbook with minimum potential to increase clinic time. These included appointments that might take less than the typical 15- or 30-minute allocation and those known as more likely to be no-shows (e.g., follow-up visits).

The QI team met with the ECU SHS staff upon the conclusion of the first semester of overbooking to assess their progress with overbooking. Approximately 7.3 percent of the SHS appointments, i.e., 920, were overbooked during the four-month semester, which resulted in a model-predicted savings of approximately $86,000. The overbooking model was used to validate the rate at which SHS overbooked. Model runs were completed at a 7.3 percent overbooking rate. The overbooking model predicted an increase in patient access of approximately 8.7 patients per day, whereas the SHS reported an actual patient-access increase of 9.2 patients per day. To statistically validate these model results, a 99 percent confidence interval was calculated around the mean patient-access increase of 8.7 patients per day, whereas the SHS reported an actual patient-access increase of 9.2 patients per day. This confidence interval for mean patient-access increase is [5.39, 12.02]. The SHS patient-access number lies within the model’s confidence interval, thus demonstrating that the overbooking model is generally valid.

Table 4: The data present a sensitivity analysis showing total utilities for various levels of waiting time per hour costs ($\rho$), Gompertz thresholds, and provider burnout costs ($\omega$). The bold in the table signifies the best utility level for a given burnout threshold and overbooking rate.

<table>
<thead>
<tr>
<th>$\omega$</th>
<th>$\rho$ value ($)</th>
<th>5%</th>
<th>10%</th>
<th>15%</th>
<th>20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega = 12.5$</td>
<td>2 50</td>
<td>850.16</td>
<td>1,502.52</td>
<td>1,836.76</td>
<td>1,653.38</td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>849.76</td>
<td>1,485.98</td>
<td>1,696.19</td>
<td>1,305.55</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>853.27</td>
<td>1,473.80</td>
<td>1,557.13</td>
<td>960.34</td>
</tr>
<tr>
<td>3 50</td>
<td>851.85</td>
<td>1,493.15</td>
<td>1,708.06</td>
<td>1,313.90</td>
<td></td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>851.24</td>
<td>1,470.18</td>
<td>1,500.78</td>
<td>799.02</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>850.83</td>
<td>1,447.96</td>
<td>1,300.33</td>
<td>289.33</td>
</tr>
<tr>
<td>4 50</td>
<td>851.19</td>
<td>1,477.88</td>
<td>1,564.86</td>
<td>963.59</td>
<td></td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>850.98</td>
<td>1,449.67</td>
<td>1,286.59</td>
<td>267.79</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>848.73</td>
<td>1,414.11</td>
<td>1,000.95</td>
<td>-421.28</td>
</tr>
<tr>
<td>$\omega = 25$</td>
<td>2 50</td>
<td>847.51</td>
<td>1,481.28</td>
<td>1,672.60</td>
<td>1,132.27</td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>849.54</td>
<td>1,470.24</td>
<td>1,540.48</td>
<td>794.48</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>848.94</td>
<td>1,453.11</td>
<td>1,400.36</td>
<td>450.20</td>
</tr>
<tr>
<td>3 50</td>
<td>847.71</td>
<td>1,470.84</td>
<td>1,544.48</td>
<td>791.57</td>
<td></td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>853.02</td>
<td>1,459.62</td>
<td>1,349.28</td>
<td>282.21</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>851.09</td>
<td>1,430.28</td>
<td>1,138.10</td>
<td>-236.71</td>
</tr>
<tr>
<td>4 50</td>
<td>850.83</td>
<td>1,462.63</td>
<td>1,412.52</td>
<td>453.56</td>
<td></td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>850.64</td>
<td>1,435.14</td>
<td>1,130.52</td>
<td>-242.05</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>847.21</td>
<td>1,396.42</td>
<td>840.44</td>
<td>-947.16</td>
</tr>
<tr>
<td>$\omega = 37.5$</td>
<td>2 50</td>
<td>851.12</td>
<td>1,474.18</td>
<td>1,527.50</td>
<td>620.53</td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>852.47</td>
<td>1,457.17</td>
<td>1,379.08</td>
<td>262.05</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>849.89</td>
<td>1,438.49</td>
<td>1,240.63</td>
<td>-72.04</td>
</tr>
<tr>
<td>3 50</td>
<td>851.32</td>
<td>1,453.90</td>
<td>1,369.96</td>
<td>264.80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>848.13</td>
<td>1,421.87</td>
<td>1,150.58</td>
<td>-253.98</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>847.02</td>
<td>1,392.77</td>
<td>919.40</td>
<td>-790.51</td>
</tr>
<tr>
<td>4 50</td>
<td>849.13</td>
<td>1,442.78</td>
<td>1,243.19</td>
<td>-76.64</td>
<td></td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>848.42</td>
<td>1,412.04</td>
<td>969.54</td>
<td>-759.20</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>847.72</td>
<td>1,379.46</td>
<td>686.17</td>
<td>-1,450.63</td>
</tr>
</tbody>
</table>
In turn, the actual savings to the SHS for the semester were approximately $95,000. The intelligent overbooking approach that the scheduler used in selecting the best time slots to overbook might provide one explanation for the actual patient increase being slightly higher than the model prediction. This information could not be captured in the model, thereby giving the actual scheduling environment a slight advantage over the simulation. Although the SHS staff members were initially concerned that overbooking would lead to very high rates of overscheduled patients and unacceptable increases in patient waiting times and provider dissatisfaction, they reported no significant problems resulting from any extended clinical sessions or increase in patient waiting time.

After experimenting with the model for a brief period in the first semester of overbooking, the SHS director told us that the SHS planned to increase to three overbooked slots per eligible provider per day in the near future (approximately a 10 percent rate of overbooking). However, the SHS kept the overbooking rate at 7.3 percent; its plans changed a few semesters after the initial overbooking implementation when the SHS decided to implement an online “open-access” scheduling-appointment system in hopes of reducing the no-show rate. The director indicated that this new type of system might help to increase efficiencies without increasing overbooking, but acknowledged that increased overbooking would be considered if desired efficiencies were not realized with open-access scheduling.

**Overbooking Project Lessons Learned**

This project was implemented by an interdisciplinary team including health-care administrators, health-care providers, and faculty in the ECU Department of Marketing and Supply Chain Management. As might be expected, the list of lessons learned that follows is dominated by organizational concerns, which were more critical than the technical issues of model development.

- The composition of the QI team was an important consideration. Those individuals known to be skeptical toward overbooking were invited to be members of the team, rather than being excluded. The final team composition included all constituencies (administrators, health-care providers, and faculty) of the client organization, and a doctor who was one of the leading skeptics. This individual later became a proponent of the model and the overbooking process.

- It was important to align the model objectives with the client organization’s decision-making process. As we engaged the client staff members, we learned that they make decisions based on trial and error results from experimental situations. In addition, the ability to reach consensus for important organizational decisions was critical. Therefore, the choice of a descriptive simulation model that facilitated effective investigation of “what-if” scenarios fit well with the clinic’s existing approaches. Large decision-support systems or optimal solutions from mathematical algorithms would not align with its management and decision processes. The model was designed to highlight the right direction for the organization; it was not necessary to provide optimal overbooking decisions.

- In this case, we saw the ability of a simple, conservative, and transparent model to convince the client organization to pursue what it believed was a controversial direction. A sophisticated OR model is not always necessary or desirable.

- Intelligent methods of overbooking a clinic schedule that are consistent with the organization’s value function can be used to minimize the negative impacts of overscheduled patients. The SHS intentionally overbooked patients early in the clinical session,
potentially increasing patient wait times but minimizing disruptions to health-care providers.

**Conclusions**

A novel overbooking model that includes the effects of employee burnout was developed to effectively communicate the consequences of overbooking appointments at a university student health-care clinic. The major costs of overbooking at this clinic consisted of provider burnout resulting from the need to see more patients than the normal capacity allowed. We used a Gompertz function to model the nonlinear relationship of these costs. Information provided by this model was instrumental in overcoming strong initial resistance to overbooking among the clinic’s health-care providers. The clinic is now selectively overbooking provider appointments, with resulting lower costs and improved health-care access to its student population.

We developed a value function to evaluate the alternative levels of overbooking the clinic, which operates as a not-for-profit. The model provides strong evidence that a 10 to 15 percent overbooking level produces the highest value. This conclusion is valid across a fairly broad range of relative valuations for patient access, \( \pi \), to provider burnout, \( \rho \). At a 10 percent overbooking level, the daily value is $1,459.62, and at a 15 percent overbooking level, the daily value is $1,349.28. Based on eight months of operation, we estimate the annual increase in value for overbooking of 10 to 15 percent to be in the range of $215,000 to $334,000.

The overbooking model was also instrumental in alleviating staff concerns about disruption and pressures that result from large numbers of overscheduled patients. At a 5 percent overbooking rate, the staff was reassured by model results that predicted 95 percent of the operating days with no patients being overscheduled; in the worst case, eight patients would be overscheduled a few days each month. In addition, at a 10 percent overbooking rate the model predicted that during 85 percent of the operating days per month, no patients would be overscheduled; a maximum of 16 overscheduled patients would rarely ever occur. Based on the model predictions, the SHS implemented an overbooking policy and overbooked by 7.3 percent with plans to increase to 10 percent in future semesters. The SHS director estimates the actual savings from overbooking during the first semester of implementation to be approximately $95,000.

We would like to highlight several project limitations for the reader. First, it was not possible to validate the model prior to presenting results to the client. We did not have access to comprehensive data on student wait times, and it also was not possible to validate provider burnout costs or increases in patient access. It was also difficult to precisely estimate the parameter values used in the model. The significance of both concerns is reduced by the fact that the model was not intended to provide optimal levels of decision support on a real-time basis. Rather, the purpose of the model was to communicate the economic advantages of overbooking and convince the client organization to pursue overbooking. Potential problems estimating the model were also offset by the client organization’s strategy of implementing overbooking in small steps. We also note that sensitivity analysis has shown the model decisions to be robust over a wide range of parameter estimates. Finally, we would like to acknowledge that the model has been improved since the initial results were presented to the client organization. These improvements have not materially affected the model conclusions.

**Appendix**

**Definition of Terms and Value Calculations**

\[ D = \text{average duration of an appointment} = \left( \text{number of } 15 \text{ – minute slots}\right) \times 15 \text{ minutes} + \left( \text{number of } 30 \text{ – minute slots}\right) \times 30 \text{ minutes} \] / \( N \).

\[ N = \text{maximum capacity of clinic (number of appointments per day)}. \]

\[ T = \text{total appointments available to the SHS}. \]

\[ OR = \text{overbooking rate} \ (0 < OR < 100\%). \]

\[ A = \text{appointments allocated by the clinic}. \]

\[ OBA = \text{number of overbooked appointments allocated by the clinic}. \]

\[ TCA = \text{total clinical appointments actually booked by the clinic prior to patient appointment demand}. \]

\[ AD = \text{appointment demand by patients}. \]
\[ B = \text{actual patient appointments accepted or booked by clinic.} \]
\[ OB = \text{actual overbooked patient appointments to the clinic after patient demand.} \]
\[ NS = \text{no-show patient appointments.} \]
\[ OS = \text{number of overscheduled patients after patient demand and no-show patient appointments.} \]
\[ NIA = \text{net increase in patients serviced because of overbooking policy.} \]
\[ MIA = \text{marginal increase in patients serviced because of overbooking policy.} \]
\[ PW = \text{cumulative patient waiting time} \]
\[ = \begin{cases} 0 & \text{if } OS = 0, \\ \text{Value from lookup table based on } OS & \text{if } OS \geq 1. \end{cases} \]
\[ LF = \text{logistic function for scaling provider burnout cost} \]
\[ = A * e^{-c(b + h + OS)}. \]
\[ PB = \text{provider burnout value pertaining to overscheduled patients} \]
\[ = OS * LF. \]
\[ \pi = \text{dollar(s) per additional patient served from overbooking,} \]
\[ \omega = \text{dollar(s) per minute of extra waiting time for an overscheduled patient,} \]
\[ \rho = \text{dollar(s) per overscheduled patient of provider burnout cost.} \]
\[ V_{PA} = \text{value of patient access} \]
\[ = \pi * MIA. \]
\[ V_{PW} = \text{value of patient waiting} \]
\[ = \omega * PW. \]
\[ V_{PB} = \text{value of provider burnout} \]
\[ = \rho * PB. \]
\[ V_T = \text{total value} \]
\[ = V_{PA} - V_{PW} - V_{OT} = \pi * MIA - \omega * PW - \rho * PB. \]

**Algorithm for SHS Overbooking and Value Generation**

**Step 1.** Initialize total # of appointments available to SHS, \( T = \text{max clinic capacity.} \)

**Step 2.** Initialize overbooking policy or rate, \( OR, \) where \( 0 < OR < \text{max\% set by clinic.} \)

**Step 3.** Clinic allocates number of clinical appointments to be made available, \( AA, \) where \( AA < T. \)

**Step 4.** Clinic allocates overbooked appointments per overbooking policy, \( OBA, \) where \( OBA = OR * AA. \)

**Step 5.** Calculate total clinic appointments actually booked by the clinic prior to patient appointment demand, \( TCA, \) where \( TCA = AA + OBA. \)

**Step 6.** Generate patient demand for appointments, \( AD, \) where \( ad \in AD \sim N(\mu, \sigma). \)

**Step 7.** Determine actual patient appointments accepted or booked by clinic, \( B, \) where
\[ B = \begin{cases} AD & \text{if } AD \leq TCA, \\ TCA & \text{otherwise.} \end{cases} \]

**Step 8.** Determine actual overbooked patient appointments to the clinic after patient demand, \( OB, \) where
\[ OB = \begin{cases} 0 & \text{if } B \leq AA, \\ B - AA & \text{otherwise.} \end{cases} \]

**Step 9.** Generate no-show patient appointments, \( NS, \) where \( NS = P * B \) and \( p \in P \sim N(\mu, \sigma). \)

**Step 10.** Calculate # of overscheduled patients after patient demand and no-show patient appointments, \( OS, \) where
\[ OS = \begin{cases} OB - NS & \text{if } OB > 0 \text{ and } OB > NS, \\ 0 & \text{otherwise.} \end{cases} \]

**Step 11.** Calculate net increase in patients serviced because of overbooking policy, \( NIA, \) where
\[ NIA = \begin{cases} \text{min}(OB, NS) & \text{if } OB > 0, \\ 0 & \text{otherwise.} \end{cases} \]

**Step 12.** Calculate marginal increase in patients serviced because of overbooking policy, \( MIA, \) where \( MIA = OS + NIA. \)

**Step 13.** Calculate patient access value, \( V_{PA}, \) where \( V_{PA} = \pi * MIA. \)

**Step 14.** Calculate patient waiting value, \( V_{PW}, \) where \( V_{PW} = \omega * PW. \)

**Step 15.** Calculate provider burnout value, \( V_{PB}, \) where \( V_{PB} = \rho * PB. \)

**Step 16.** Calculate the total value associated with overbooking, \( V_T, \) where \( V_T = \text{total value} = V_{PA} - V_{PW} - V_{PB} = \pi * MIA - \omega * PW - \rho * PB. \)

**Step 17.** Determine optimal overbooking policy via maximizing overall value \( \text{Max } V_T(OR) = \text{max}(V_T|OR_1, V_T|OR_2, V_T|OR_3, \ldots, V_T|OR_n). \)

**Example Algorithm for SHS Overbooking and Value Generation**

**Step 1.** Initialize total # of appointments available to SHS, \( T = 168. \)
**Step 2.** Initialize overbooking policy or rate, OR = 7.3 percent.

**Step 3.** Clinic allocates # of clinical appointments to be made available, AA = 168.

**Step 4.** Clinic allocates overbooked appointments per overbooking policy, OBA = 13.

**Step 5.** Calculate total clinic appointments actually booked by the clinic prior to patient appointment demand, TCA = 181.

**Step 6.** Generate patient demand for appointments, AD = 218.

**Step 7.** Determine actual patient appointments accepted or booked by clinic, B = 181.

**Step 8.** Determine actual overbooked patient appointments to the clinic after patient demand, OB = 13.

**Step 9.** Generate no-show patient appointments, NS = 10.

**Step 10.** Calculate # of overscheduled patients after patient demand and no-show patient appointments, OS = 3.

**Step 11.** Calculate net increase in patients serviced because of overbooking policy, NIA = 10.

**Step 12.** Calculate marginal increase in patients serviced because of overbooking policy, MIA = 13.

**Step 13.** Calculate patient access value, \( V_{PA} = \$1,781.00 \).

**Step 14.** Calculate patient waiting value, \( V_{PW} = \$152.34 \).

**Step 15.** Calculate provider burnout value, \( V_{PB} = \$225.04 \).

**Step 16.** Calculate the total value associated with overbooking, \( V_T = \$1,403.62 \).

### Algebraic Derivation of the Gompertz Curve Parameters

From this information, the number of overscheduled patients for the upper inflection point was set at 10 (\( x_1 = 10 \)), and the number of overscheduled patients for the lower inflection point was set at 3 (\( x_2 = 3 \)). Subsequently, \( Y_{y1} = 1 \) and \( Y_{y2} = 2.95 \) are the provider burnout factors associated with those levels of overscheduled patients. The Gompertz curve equation parameters are then the solution of a set of two nonlinear simultaneous equations:

\[
Y_{y1} = A \cdot e^{−e^{−(b_0 + b_1 x_1)}}; \quad (10)
\]

\[
Y_{y2} = A \cdot e^{−e^{−(b_0 + b_1 x_2)}}. \quad (11)
\]

By modifying and substituting in the original Equations (10) and (11), the solutions for \( b_0^* \) and \( b_1^* \) can be found. Using Equation (12), \( b_0^* \) may be derived. Substituting \( b_1^* \) into Equation (13) gives \( b_1^* \).

\[
b_0^* = \frac{−\ln(\ln(−\ln(Y_{y1})) − b_1)}{x_2}; \quad (12)
\]

\[
b_1^* = \frac{−\ln(\ln(−\ln(Y_{y1})) − b_1 x_1)}{x_1}. \quad (13)
\]

The numeric parameters for \( b_0^* \) and \( b_1^* \) can be found using matched pairs of \((x, Y_y)\), based on the points of inflection of the S curve. One of these matched pairs is substituted into Equation (13) to find \( b_0^* \). Then \( b_0^* \) is used with the other matched pair to find \( b_1^* \). The Gompertz S curve function for an upper level of three is as follows in Equation (14):

\[
Y_{UL3} = 3e^{−e^{−(−1.89+0.5072x_1)}}. \quad (14)
\]

### References


Barron, W. M. 1980. Failed appointments: Who misses them, why they are missed, and what can be done. *Primary Care* 7(4) 563–574.


Jolene Jernigan, RN-C, FNP, Director East Carolina Student Health Clinic, 1001 East 5th Street, Greenville, North Carolina 27858-4353, writes: “I am writing on behalf of the East Carolina University Student Health Service to express appreciation for the vital contribution of professors John Kros, Scott Dellana, and David West to the SHS Quality Improvement team effort of developing an Excel spreadsheet overbooking model. This model has been an invaluable aid for our staff to understand the issues of overbooking our clinic schedule.

“The Student Health Service schedules approximately 35,000 appointments each year for health care needs. A number of these appointments result in no-shows when students do not arrive for scheduled appointments. During peak periods we experience in excess of 450 no-shows a month, a no-show rate of 10% to 15%. No-shows waste our organization’s capacity and idle valuable healthcare providers. Based on an average cost of $137 per patient visit, I estimate the gross cost of no-shows to the Student Health Service as much as $400,000 annually.

“Our staff recognized that a policy of overbooking appointments had the potential to reduce idle time and costs. However, early discussions among staff members revealed a resistance to overbooking appointments because of the unique and critical importance of timely health care services. At a meeting on October 5, 2005, Dr. Kros demonstrated the spreadsheet overbooking model to the SHS staff, discussing the benefits and consequences of overbooking the clinic schedule by 5%, 10%, and 15%. The Excel spreadsheet model was transferred to the staff at that meeting; some of them subsequently experimented with the model, performing their own analysis.

“The presentation and the spreadsheet model were critical to overcoming staff objections to overbooking appointments. We began overbooking the schedule during the Spring 2006 semester by 1 morning and 1 afternoon appointment for each medical provider. I estimate the value of the recovered appointments from this overbooking policy to be about $150,000 annually. The number of overscheduled students varied between 0% and 4% daily, a level close to the spreadsheet model prediction.

“We are currently using the spreadsheet model to prepare for an increased level of overbooking approaching the 10% level for the Fall 2006 semester and expect to achieve additional benefits.”