INTRODUCTION
Patient absenteeism for scheduled appointments—also called “no-shows”—occurs frequently in healthcare systems worldwide, with rates at outpatient clinics ranging from 12 to 80% depending on the type of procedure (1–15). Patient no-shows can lead to diminished productivity and revenue losses for clinics, and reduced care satisfaction and treatment delays for patients. Although many approaches have been used to address the problem of patient absenteeism—including telephone reminders, mailings, text messages, and patient navigator programs—these approaches yield modest or inconsistent improvements in attendance (16–22). Fining patients for no-shows has demonstrated better success, but this punitive solution is not ideal for patients with limited financial resources (7).

The travel and lodging industries address the problem of no-shows by “overbooking” at fixed, average historical rates. When applied to the healthcare setting, fixed overbooking could overburden staff on days where more patients show for appointments than expected, leading to increased patient wait times and lower care satisfaction (8,23). Also, a healthcare provider should not turn away patients in need of vital health services.

As opposed to fixed overbooking, a healthcare setting may benefit most from solutions that assess the absenteeism risk of individual patients rather than the whole clinic. Previous studies

OBJECTIVES: Patient absenteeism for scheduled visits and procedures (“no-show”) occurs frequently in healthcare systems worldwide, resulting in treatment delays and financial loss. To address this problem, we validated a predictive overbooking system that identifies patients at high risk for missing scheduled gastrointestinal endoscopy procedures (“no-shows” and cancellations), and offers their appointments to other patients on short notice.

METHODS: We prospectively tested a predictive overbooking system at a Veterans Administration outpatient endoscopy clinic over a 34-week period, alternating between traditional booking and predictive overbooking methods. For the latter, we assigned a no-show risk score to each scheduled patient, utilizing a previously developed logistic regression model built with electronic health record data. To compare booking methods, we measured service utilization—defined as the percentage of daily total clinic capacity occupied by patients—and length of clinic workday.

RESULTS: Compared to typical booking, predictive overbooking resulted in nearly all appointment slots being filled—2.5 slots available during control weeks vs. 0.35 slots during intervention weeks, t(161)=4.10, \( P=0.0001 \). Service utilization increased from 86% during control weeks to 100% during intervention weeks, allowing 111 additional patients to undergo procedures. Physician and staff overages were more common during intervention weeks, but less than anticipated (workday length of 7.84 h (control) vs. 8.31 h (intervention), t(161)=2.28, \( P=0.02 \)).

CONCLUSIONS: Predictive overbooking may be used to maximize endoscopy scheduling. Future research should focus on adapting the model for use in primary care and specialty clinics.

PREVENTING ENDOSCOPY CLINIC NO-SHOWS: PROSPECTIVE VALIDATION OF A PREDICTIVE OVERBOOKING MODEL

Mark W. Reid, PhD, Folasade P. May, MD, MPhil, Bibiana Martinez, MPH, Samuel Cohen, MD, Hank Wang, MD, MSHS, Demetrius L. Williams Jr, MPA and Brennan M.R. Spiegel, MD, MSHS

OBJECTIVES: Preventing Endoscopy Clinic No-Shows: Prospective Validation of a Predictive Overbooking Model

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As opposed to fixed overbooking, a healthcare setting may benefit most from solutions that assess the absenteeism risk of individual patients rather than the whole clinic. Previous studies

1Department of Gastroenterology, VA Greater Los Angeles Healthcare System, Los Angeles, California, USA; 2Cedars-Sinai Center for Outcomes Research and Education (CS-CORE), Los Angeles, California, USA; 3Division of Digestive Diseases, David Geffen School of Medicine at UCLA, Los Angeles, California, USA; 4Kaiser Permanente Northern California, Oakland, California, USA; 5Department of Health Policy and Management, UCLA Fielding School of Public Health, UCLA, Los Angeles, California, USA; 6Department of Medicine, Cedars-Sinai Medical Center, Los Angeles, California, USA. Correspondence: Brennan M.R. Spiegel, MD, MSHS, Pacific Theatre Building, 116 North Robertson Boulevard, 4th Floor, Los Angeles, California 90048, USA. E-mail: brennan.spiegel@cshs.org

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have reported that a patient may miss an appointment for several measurable reasons, including previous absenteeism, active mental health comorbidities such as depression or substance abuse, poor access to transportation, or other socioeconomic problems (9,10,12,24–31). Probabilistic computer simulations that overbook based on these patient-level characteristics demonstrate that predictive overbooking may improve clinic service utilization rates and reduce idle staff time, but may also increase patient wait times and staff overtimes when the predicted availabilities are higher than actual no-shows (14,32,33).

In our previous research, we retrospectively demonstrated that a predictive overbooking system utilizing patient-level data obtained from an electronic health record (EHR) has the potential to optimize clinic throughput while leading to rare clinic overflows (34). We validated our predictive overbooking model prospectively over a 34-week period at a Veterans Affairs (VA) healthcare network outpatient gastrointestinal (GI) endoscopy clinic—a VA-funded effort to improve access to care and help address recent concerns about scheduling in the VA Healthcare System (35). We also chose this setting because it is a model high-throughput, resource-intense environment commonly affected by patient no-shows (5,6,19,31,36–40). Although we made accurate predictions about upcoming clinic availability, we were only able to successfully book 69 patients into over 300 slots projected to be available.

For the current study, we prospectively implemented a two-pronged strategy for quickly booking patients into outpatient endoscopy appointments predicted to be open using our previously developed patient absenteeism model. We scheduled patients through a weekly outpatient GI clinic, and also developed an electronic consultation request that could be completed by a patient’s primary care provider (PCP) during a visit where endoscopy was recommended. On the basis of the previous performance of the model, we hypothesized that the rate of service utilization would increase compared to status quo scheduling. We prospectively tested this hypothesis in an interrupted time series comparing predictive overbooking to “one patient, one slot” scheduling.

METHODS
Study overview and design
In our previous work (34), we used patient- and clinic-level data obtained retrospectively over an 8-month period to develop a predictive model for patient absenteeism, and validated the model compared to a fixed overbooking approach using additional patient data collected over a 4-month period. In the current study, we implemented the predictive overbooking system using an active recruitment strategy to allow patients to complete endoscopies within 2 weeks of recommendation—the current treatment goal for VA patients (41). We tested the predictive overbooking system during 17 randomly selected weeks over a 9-month period in an interrupted time series design. Our goal was to evaluate how using predictive overbooking would affect clinic service utilization rates, staff workflow, and clinic costs.

Patients
All patients in this study were United States military Veterans scheduled for outpatient endoscopy (primarily esophagastroduodenoscopy and colonoscopy) in the VA Greater Los Angeles Healthcare System, a geographically and demographically diverse network of 15 clinics jointly serving 1.4 million Veterans. We collected data for 2,446 patients scheduled between March and November 2014. All data were collected in a VA-approved database and obtained through automated searches of the VA EHR. Study design and procedures were formally reviewed and approved by the VA Institutional Review Board (VA IRB # CC 2013-040489). Participants provided verbal consent during the intervention phase after receiving and reviewing study information, risks, and benefits. We did not offer patient compensation.

Predictor variables and model
We obtained patient data from the VA Computerized Patient Record System, including demographics, clinical diagnoses, and patient attendance histories (Table 1 for a list of variables employed in the predictive model). Demographic variables included age, race, level of VA cost coverage (i.e., percentage of service connectedness), and socioeconomic status. Clinical variables were both GI-specific (e.g., previous endoscopy) and general (e.g., recent diagnosis of depression). We automatically processed raw text from patients’ active problem lists and procedure histories to flag ICD-9 codes associated with particular diagnoses or treatments, and we generated dichotomous variables for each relevant condition. We limited clinical history reviews to the most recent 3 years of data available for a given patient. We also calculated the Charlson Comorbidity Score—a measure of patient mortality risk that incorporates cardio- and cerebrovascular diseases, GI diseases, cancer, and other severe ailments into a single index value—to capture overall disease burden for each patient (42). We obtained GI appointment attendance variables from the

<table>
<thead>
<tr>
<th>Variable</th>
<th>Multivariable test statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charlson Comorbidity Index Score</td>
<td>0.001</td>
</tr>
<tr>
<td>Previous GI procedure no-show</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Cancellation proportion for all appointments</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Multiple procedures scheduled on same day</td>
<td>0.03</td>
</tr>
<tr>
<td>Mood disorders Dx in last 2 years</td>
<td>0.02</td>
</tr>
<tr>
<td>Other substance use Dx in last 2 years</td>
<td>0.03</td>
</tr>
<tr>
<td>Any GI procedure completed in last 3 years</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

CI, confidence interval; Dx, diagnosis; OR, odds ratio; GI, gastroenterology. Final logistic regression model includes all variables listed above.
endoscopy clinic scheduling software—endoPRO iQ (Pentax Medical, Montvale, NJ, USA). We recorded presence or absence of any cancellations or no-shows for any GI appointment during the previous 2 years. Using the Computerized Patient Record System data, we also computed a ratio for each patient of all canceled or missed appointments across the entire VA healthcare system to the total number of clinic appointments booked (“cancellation proportion” in Table 1).

We detailed the methods used to develop our predictive model in our previous work (34). In short, we evaluated the predictive power of many demographic, clinical, and behavioral (i.e., appointment attendance) variables in simple logistic regression models, and eliminated variables that did not explain unique variance in patient attendance. Our final model contains seven key predictor variables entered in a logistic regression equation, which produces a no-show risk score for each patient. We recalculated risk scores weekly, incorporating the most recent patient data into each week’s projections. On the basis of the equation, patients whose no-show probability exceeded 0.45 were estimated to miss their upcoming appointments, as this value had maximized specificity during the predictive model receiver operating characteristic curve analysis.

Patient recruitment
Over a 34-week period, we collected data weekly on all patients with appointments booked during the following 2-week period, and used the logistic regression model developed in our previous study to calculate a no-show probability score for each patient. During a randomly selected subset of 17 weeks, we generated a 2-week calendar of projected open appointments (i.e., those originally made for patients with no-show risk scores above 0.45), separated into morning and afternoon times. We offered these projected open appointments to patients using an active recruitment strategy we called “Fast Track,” involving two methods—(i) at a weekly GI outpatient clinic, a research staff member stationed next to the appointment scheduler would explain the study risks and benefits, and offer the patient an open appointment during the next 2 weeks; (ii) at a visit with a PCP, who viewed an electronic consult request explaining the study embedded in the EHR in which the PCP could select to fulfill a recommendation for an endoscopy. Patients who opted to participate in “Fast Track” overbooking through their PCP were subsequently contacted by the GI clinic scheduler or a research staff member, who scheduled the appointment and explained risks and benefits. If patients who opted into “Fast Track” scheduling were not given bowel preparation in a timely manner (i.e., able to pick it up within the 2-week interval between recommendation and appointment), their consult requests were forwarded to typical scheduling.

In all cases, we did not book patients into the specific appointment slots that other patients were projected to miss. Instead, we allowed patients to designate a morning (0730–1130 hours) or afternoon (1230–1630 hours) option. Patients were only offered appointments during the 2 weeks following the day of contact with the scheduler, and they had to agree to the following two conditions: (i) on the date of the appointment, the patient may have to wait longer (due to a potential backlog of patients who unexpectedly attended appointments); and (ii) if the appointment did not require consumption of bowel preparation, or was not urgent, the patient’s appointment may be rescheduled to the next available time. Patients who were not interested in this arrangement were booked using typical scheduling methods. Typical scheduling methods consist of booking a patient for the next available appointment on a desired time and day, which was often 30–60 days after the data of contact with the scheduler. All patients with upcoming appointments received personal reminder calls 10, 5, and 1 day before the appointment, and reminder postcards were sent to most patients 7 days before the appointment.

Outcome variables and statistical analysis
We collected data on clinic utilization from endoPRO iQ, recording the earliest start time and latest end time for appointments each day, as well as the number of clinic staff on duty at the end of each day. We also obtained hourly pay rates for clinic staff in order to calculate the added staff cost of operating the predictive overbooking system.

We calculated daily clinic utilization by calculating the ratio of the number of appointments completed to the number of appointments available per day. We counted a week as an intervention week if at least one patient had been booked for that week using the Fast Track system, including all days when Fast Track appointments were available but not used. We counted a week as a control week if no patients opted into projected openings, or if we were not recruiting patients during that week.

In our previous work (34), we compared performance of the predictive overbooking model to the performance of various fixed overbooking rates (ranging from 19 to 38%, based on historical averages), and in general observed that fixed overbooking was more difficult because of the ever-changing composition of clinic patients. For the current study, we compared the performance of intervention weeks to control weeks, as this design was easier to implement in a working clinic. We compared both the daily clinic service utilization rates between intervention and control phases, the lengths of workdays (in hours), and operating costs by day using the Student’s t-test. We compared differences in demographic variables using chi-squared tests and the Student’s t-test, when appropriate. All analyses were conducted using Stata version 13.1 (Statcorp, College Station, TX, USA).

Role of the funding source
This study was funded by a VA Health Services Research and Development (HSR&D) Merit Award (IIR 12-055). The VA was not responsible for the design, conduct, or reporting of data from this study.

RESULTS
Implementation of predictive overbooking
We collected data on all patients who completed appointments during the study period (N=2,446). An additional 146 patients missed appointments during this period, but were not rebooked; their data have been removed from analysis. A total of 1,181
completed appointments were booked during the control phase, and 1,265 were booked during the intervention period. Demographic information about control and intervention participants is reported in Table 2. Among the patients who booked appointments during the intervention phase, 111 accepted Fast Track appointments, and most of these were booked during the weekly GI clinic (n=75; 68%) rather than via the PCP (32%).

Demographic differences between fast track participants and the study population

The 111 patients who opted into a Fast Track appointment were significantly different from the rest of the study population in terms of demographic, clinical, and socioeconomic variables. Specifically, Fast Track patients were more likely to report African-American race (P=0.05), greater VA service connectedness (P=0.008), lower overall disease burden (P=0.01), and were less likely to report recent history of mood disorder (P<0.0001) or socioeconomic difficulties (P<0.0001). Further, individuals who declined to report race or ethnicity were also significantly less likely to opt into Fast Track overbooking appointments.

Effects of predictive overbooking on service utilization

Application of the predictive overbooking scheduling system significantly improved rates of service utilization, defined as the ratio of completed appointments to capacity on a given day. Figure 1 displays the weekly average of performance of the predictive overbooking model, comparing intervention weeks to control weeks. On average, predictive overbooking increased the service utilization rate from 86.4 to 99.5%, allowing 111 additional patients to receive endoscopies during the 17 weeks the calendar was implemented in the study period. Under typical “one patient, one slot” scheduling, an average of 2.5 appointments were left unused every day. When the predictive overbooking calendar was utilized, roughly one-third of an appointment was left unused every day (−2.5 vs. −0.35; difference =−2.15; 95% CI: −3.19 to −1.11; P=0.0001).

Effects of predictive overbooking on staff workday length and overtime

During intervention weeks, clinic capacity was underfilled on 37 days, and filled to exact capacity on 9 days. On the 37 days where appointments exceeded capacity, the overage was between one and two appointments on most days (median=1; range=1–10; Figure 2a). During control weeks, the number of procedures performed per day over clinic capacity was reduced compared to intervention weeks, but 14 days exceeded capacity, whereas other days were far under capacity (Figure 2b).

Even though capacity was exceeded on several occasions during intervention weeks, the impact on clinic staff schedules was minimal. The clinic workday averaged 8.14h on the seven intervention days that exceeded capacity by four or more appointments, and averaged 8.73h on the nine control days that exceeded four or more appointments. On average, intervention clinic days were 34 min longer than control days (8.31h vs. 7.84h, difference =0.47; 95% CI: 0.06–0.88; P=0.02), reflecting increased clinic utilization. We did not formally survey clinic staff about the effects of predictive overbooking on morale, but we also did not receive any complaints about our efforts.
Effects of predictive overbooking on clinic costs

Other than costs associated with preparing and testing the predictive model, the costs of the predictive overbooking program amount to what is paid to clinic staff who must work overtime to complete procedures. Assuming that all patients in the clinic after 1630 hours were treated by exactly one nurse and one technician for the duration of their visits, we can estimate the overtime costs associated with the predictive overbooking system. With nurses paid at a rate of $75/hour, and technicians paid at a rate of $35/hour during overtime, the average overtime cost during the control phase was $36.88; the average overtime cost during the intervention phase was $63.01. Although the program costs $26.13 more per day to operate, this amount is not statistically distinct from the existing overtime costs associated with the clinic ($t(161)=1.60, P=0.11$). Distributed over the 111 patients recruited for Fast Track appointments, each additional patient cost the clinic $19.53 to treat, on average.

**DISCUSSION**

In the current study, we demonstrate that a predictive overbooking system that utilizes EHR data to predict patient no-show can increase rates of service utilization effectively, offsetting the problem created by frequent patient absenteeism for appointments. The system does not require patient involvement for data collection and no-show risk calculation, but it does require intervention by clinic staff to book patients into projected openings. The primary issue we addressed with the current study was how to translate a mathematical no-show prediction rule into actual clinic performance improvements. This accomplishment requires time investment from clinic staff, in the forms of additional scheduling and completion of additional procedures.

In this study we found that only a small number of additional bookings ($n=111$) was enough to maximize utilization. Over the last 4 years, throughput at this clinic was as low as the 1st percentile compared to other comparable clinics, but improved to the 33rd percentile during the study. Although the 111 patients we recruited were just a part of this overall performance improvement, the small number was a statistically significant improvement and contributed to this positive change. During our previous
study, the no-show rate fluctuated between 19 and 38%, and was as low as 15% during the control period. The predictive overbooking system excelled most at addressing the problem of no-shows dynamically, allowing for continuous adjustments to the projected no-show rate for a given day, regardless of other factors driving clinic performance. In contrast, a fixed overbooking percentage based on historical averages would have been problematic during the current study, consistently overfilling the clinic and overburdening clinic staff.

We evaluated the no-show predictive overbooking model in a GI clinic, where many patients were scheduled for a colonoscopy. This procedure, in particular, is often negatively stigmatized, given its invasive nature and substantial preparation steps. Although GI clinics are commonly impacted by a high no-show rate (5,6,19,31,35–39), other clinics offering less stigmatizing services may not see such dramatic changes in patient attendance if they were to employ a predictive overbooking model. Nonetheless, GI endoscopy clinics offer a proof-of-principle setting to test the predictive overbooking model in a challenging environment.

Limitations
This study has limitations primarily related to treatment setting, which restrict its generalizability. The patient population examined was scheduled for appointments at a single GI clinic at a VA hospital in the Western United States. Because the population was predominantly male and regularly received medical care at the VA, we could not examine the effects of gender or other insurance coverage. We do not suspect that female patients would behave differently, but we assume that patients with greater socioeconomic status may not attend appointments for a different set of reasons. Future research should focus on predicting absenteeism in patients who are treated in other healthcare settings. On the other hand, the VA healthcare setting allowed us to gather detailed information about previous medical diagnoses and appointment attendance across all medical specialties, which were vital predictors of patient absenteeism in our overbooking model. In order to apply a comparable model in a patient population served by diverse care providers (rather than a managed care provider like the VA), clinic staff would need to gather accurate information about patient attendance and medical history.

In addition, this study is limited by the demographic representativeness of the patient sample, as well as the intervention duration. The sample recruited for Fast Track participation was demographically distinct from the study population. Although we are encouraged by increased service uptake by African Americans—a group well documented to receive low levels of colonoscopic screening for colorectal cancer (43)—we are discouraged by the lack of uptake among individuals with low socioeconomic status. Future iterations of this project will address this problem in the context of patient recruitment and retention. Also, we did not compare predictive overbooking over a whole year to traditional overbooking during another year. This design prevents us from examining seasonal trends, but also allowed us to control for ersatz booking procedures implemented by clinic staff to increase clinic utilization over the course of the study period. For example, some appointment schedulers overbooked patients from a waitlist during the course of the study period, whether our study was in an intervention week or not. This difficulty was unavoidable in this pragmatic trial, as the mission of the VA is to serve patients first. However, this difficulty would also support the null hypothesis, where such non-protocoled booking efforts would be equally distributed over all service weeks. Instead, we randomly selected weeks during the entirety of these additional booking efforts, and demonstrated a significant effect uniquely attributable to Fast Track overbookings.

We also did not formally assess any impact on staff morale during the intervention weeks. Although the average intervention workday was approximately 30 min longer compared to workdays during control weeks, we did not field any major complaints from patients or staff. Indeed, during a day of unusually high-clinic volume (Figure 2a), Fast Track was implicated and then absolved of blame for the high-clinic volume; although this workday was busy, it did not end significantly later than other high-volume days. Anecdotally, predictive overbooking did not bother staff, and its permanent implementation has been supported by hospital management.

Conclusions
Despite these shortcomings, we believe that the predictive overbooking methods may serve as a model for other resource-intensive clinics with high no-show rates. Given the availability of sufficient information in the EHR, patients can be profiled easily, but they must be actively recruited by clinic staff in order to maximize clinic performance. Future research should evaluate whether this EHR-based predictive overbooking strategy may be effective in other types of clinical settings, where detailed information about patient attendance and medical background may be more difficult to obtain. Even limited attendance data and a questionnaire about health history will give clinics with limited data resources a chance to improve patient throughput.

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CONFLICT OF INTEREST
Guarantor of the article: Mark Reid, PhD and Brennan Spiegel, MD, MSHS.
Specific author contributions: Mark Reid planned and conducted the study, collected and interpreted data, and drafted the manuscript. Fola May planned the study, interpreted data, and drafted the manuscript. Ms Bibiana Martinez planned and conducted the study, collected and interpreted data, and edited the manuscript. Samuel Cohen collected and interpreted data, and edited the manuscript. Hank Wang planned the study, interpreted data, and edited the manuscript. Mr Demetrius Williams Jr conducted the study, collected and interpreted data, and edited the manuscript. Brennan Spiegel planned and conducted the study, collected and interpreted data, and drafted the manuscript. All authors approved the final draft of this manuscript.
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Potential competing interests: None.

Study Highlights

**WHAT IS CURRENT KNOWLEDGE**
- Absenteeism for scheduled endoscopy procedures is common and costly.
- Reminders and patient fines address absenteeism inconsistently.
- Fixed overbooking may overfill the clinic or deny vital patient services.
- Previous research on patient absenteeism suggests that electronic health record (EHR) data can be used to predict no-shows and cancellations.

**WHAT IS NEW HERE**
- Previous absenteeism, comorbid disease burden, and current mental illness accurately predict no-shows and cancellations in a working clinic.
- Predictive overbooking can improve service utilization rates from 86 to 100%, allowing dozens of additional patients to be seen on short notice.
- Clinic capacity can be maximized on most days, with minimal and manageable clinic overflow.

REFERENCES