12-2010

Using No-Show Modeling to Improve Clinic Performance

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Funding Received: This work was supported by a grant from the National Science Foundation (0729463) to Drs. Lawley and Sands.

Alternative Title: Use of No-Show Modeling in Clinical Scheduling

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Word count: 4,173

Number of Figures: 4

Number of Tables: 3

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Abstract

'No-shows' or missed appointments result in under-utilized clinic capacity. We develop a logistic regression model using electronic medical records to estimate patients' no-show probabilities and illustrate the use of the estimates in creating clinic schedules that maximize clinic capacity utilization while maintaining small patient waiting times and clinic overtime costs. This study used information on scheduled outpatient appointments collected over a three-year period at a Veterans Affairs medical center. The call-in process for 400 clinic days was simulated and for each day, two schedules were created: the traditional method that assigned one patient per appointment slot and the proposed method that scheduled patients according to their no-show probability to balance patient waiting, overtime and revenue. Patient no-show models together with advanced scheduling methods would allow more patients to be seen a day while improving clinic efficiency. Clinics should consider the benefits of implementing scheduling software that include these methods relative to the cost of no-shows.

KEY WORDS: MISSED APPOINTMENTS, NO-SHOWS, PATIENT SCHEDULING, PREDICTIVE MODELS

Introduction

A ‘no-show’ results when a patient misses an appointment without cancelling. Moore reported that no-shows wasted 25.4% of scheduled time in a family medicine clinic and cost clinics 14% of anticipated daily revenue.[1] In addition, no-shows result in longer appointment lead times and lower provider productivity, patient satisfaction, and quality of care.[2-3] In primary care settings, no-show rates range from 14% to 50%.[4-7]

Two approaches have been used to address the no-show problem. One approach is focused on changing patient behavior through education, sanctions, and reminders.[5] Typically, education and reminders result in only modest reductions in no-show rate (i.e. 10% in absolute difference).[8-11] Patient sanctions such as charging a no-show fee are a less desirable solution because they can limit access to care to patients with restricted income. Another approach is focused on scheduling patients so as to reduce the impact of no-shows on clinic efficiency. This approach includes methods such as overbooking and short lead-time scheduling.

Typically, overbooking involves scheduling an additional fixed number of clients each day based on the clinic no-show rate. This type of scheduling is associated with increased wait time for patients during clinic sessions, [2] which could worsen clinic no-show rates.[12-13] In addition, this type of scheduling is also associated with increased clinic overtime which could negatively affect clinic revenue.[2]

Another scheduling method aimed at mitigating the effect of no-shows is short lead-time scheduling which allows patients to see their physician within a day or two of scheduling the appointment. In theory, short lead times should reduce no-shows and increase patient access to healthcare.[14] However, results are mixed as to whether this type of scheduling method works. Some studies report no reduction in no-show rates, other studies report that it works for some clinics in their system, but not for others.[6] Studies also suggest that the effects of local clinic conditions and patient demographics may affect the success of this type of scheduling on reducing no-show rates.[14-15] These mixed results provide evidence that future scheduling methods should consider factors that affect no-show status other than lead time such as patient characteristics.

To date, prior studies have not described clinic scheduling methods that considered how each patient's probability for not showing to their general practice medical appointment might be used to optimally schedule patients during the day so as to minimize clinic overtime while simultaneously maximizing provider productivity and clinic revenue.[16] No-show patients tend to be younger [17-19], unmarried [20], uninsured [18-20], with psychosocial problems [21-23] and a history of no-showing.[24] Appointment characteristics associated with no-showing include lead time [25-29] and the day and time of the scheduled appointment.[27, 30] Other factors include access to transportation [26, 30] and clinic proximity.[19]

Although many studies report factors associated with no-showing to an appointment, few were conducted with general medical practice patients and even fewer attempt to incorporate estimated no-show probabilities into a scheduling system. Studies that modeled no-show behavior of general medical practice patients were published long ago and included only a few predictor variables in the no-show model.[16, 31] In more recent work, Glowacka et al.(2009) use a rule-based approach to determine patients' no-show probabilities and they use these results to help determine the optimal number of patients to schedule per clinic session which may include some overbooking.[32] The association rule mining (ARM) technique they use only assigns some patient groups a no-show probability and in fact only gives a no-show probability for 21.6% of patient visits (390/1809). Average no-show rates for the unclassified patient visits grouped by day of week and specialty are used to fill-in what is not provided by their model.[32] In contrast, we use logistic regression to obtain patient specific no-show probabilities thus everyone in our dataset without missing data is assigned a no-show probability. Patients with missing data could be assigned the average clinic no-show rate for scheduling purposes. In addition, the Mu-Law scheduling method proposed herein is a stochastic method that builds the schedule sequentially through a call-in process whereas most scheduling methods are based on assuming the complete set of patients to be scheduled is known when scheduling decisions are being made.[33] Thus our method builds on the previous studies by assessing all factors that may contribute to the probability of no-showing and illustrating how clinic efficiency can be improved through an advanced clinic scheduling system that includes stochastic overbooking.

Methods

No-Show Modeling

Participants Data were obtained from outpatient clinics at a Midwestern Veterans Affairs (VA) hospital in the United States. Missed appointments were logged into the Resource Management Service (RMS) database by the appointment clerk on the day of the no-show. The data included information on 32,394 visits from 5,446 patients collected over a three-year period. Approval for human subjects' research was obtained from Purdue University.

Explanatory Variables Table 1 provides the list of factors considered. Patient co-morbidities and demographics were obtained from the Veterans Health Information Systems and Technology Architecture (VISTA) database. Demographic variables included age (in deciles ≤ 50 years to > 70 years), marital status (married or single/widowed/divorced), and patient travel distance to the clinic (≤ 6, 7-90, >90 miles). Other variables included patient insurance coverage (Medicare/private or other) and percent of costs covered by the VA. Although the percent of costs covered by the VA was provided as categorical data (< 20%, 20-60%, and > 60%), it was modeled as continuous with values of 0, 1, and 2 since the percentage of no-shows decreased linearly. Co-morbidities and clinical characteristics are also listed in Table 1. A cardiac condition was defined as coronary artery disease, myocardial infarction, or atrial fibrillation. A Charlson co-morbidity index was also constructed to capture the number and severity of co-morbidities. [34] A weight is assigned to each co-morbidity (weights are based on one-year mortality) and these weighted co-morbidities are summed for each patient to obtain their Charlson co-morbidity index which ranges between 0 and 27 with the majority falling below 3.

Several predictor variables were developed from the appointment data. These included the days since last visit, the appointment lead time, the prior no-show rate, and total number of previous visits categorized as (1-3, 4-6, >6) . The weekday, appointment time (morning, afternoon), and season were also explored as predictor variables.

Development of Predictive Model Figure 1 (top) describes the method we used to develop the model. Patient data were randomly divided into development and validation cohorts (⅔ and ⅓ of the data, respectively). The development cohort was used to develop the logistic regression model to estimate a patient's no-show probability. The development cohort contained 21,692 appointments for 3,631 patients. The last visit for each patient was used for modeling no-show because the co-morbidities pertain to the most recent visit. Patients with one appointment (n=147) were omitted since one appointment was not sufficient to estimate past no-show behavior. SAS® V.9.1 (SAS Institute Inc., Cary, NC) was used for all analyses. Bivariate associations with no-show were computed (see Table 1), with likelihood ratio chi-square tests being reported for categorical variables and t-tests for continuous variables.

Variables were considered as candidates for inclusion in the multivariable logistic regression if the p-value from their bivariate test was less than 0.25.[35] The full logistic regression model included all candidate variables plus the number of prior visits, prior no-show rate, and their interaction. For model building purposes, the number of prior visits, prior no-show rate, and their interaction were kept in all models. Backward model selection with a threshold of $p = .05$ was used to determine a reduced logistic regression model. From the multivariable logistic regression model we can estimate the no-show probability for each individual.

Validation of Predictive Model Figure 1(bottom) describes the process for validating the model in scheduling. Validity assessments determine whether the estimated no-show probabilities accurately reflect patient behavior. The purpose of this model is to use the no-show probability estimates for a daily schedule of patients. Therefore, a validation method derived from the theory of Monte Carlo simulation was developed.[36] First, 1000 samples of size 30 (the average number of patients seen daily by a physician) were randomly selected (with replacement) from the validation cohort. Then, for a given sample, the expected number of no-shows was computed and compared to the actual number of no-shows.

Appointment Scheduling Using No-Show Probabilities

To demonstrate the utility of incorporating no-show modeling in clinical scheduling, 400 patient call-in sequences were simulated by randomly drawing, with replacement, from the validation cohort. For each sequence, two schedules were created. The first schedule assigned one patient to each slot without regard to no-show probability (referred to as One/slot). The second schedule was created using the method developed by Muthuraman and Lawley (referred to as Mu-Law).[33]

In Muthuraman and Lawley (2008), the authors randomly generate the no-show data. They consider a number of patient types with different no-show probabilities, assign weights to each patient type and generate the call-in sequences based on these weights. For example, if three patient types with no-show probabilities of 0.1, 0.5 and 0.9 and weights of 0.60, 0.30 and 0.10 are considered, the average no-show probability will be 30% (0.1*0.60 + 0.5*0.30 + 0.9*0.10 = 0.3). For that example, 60% of the time the patient will have a no-show probability of 0.1, 30% of the time the patient will have a no-show probability of 0.5 and 10% of the time the patient will have a no-show probability of 0.9. Their method uses no-show, service time, and slot length information, together with patient waiting costs, overtime costs, and patient revenue to make slot assignments that optimally balance patient waiting time, clinic overtime, and patient revenue.

Based on our experience with several mid-western medical clinics, the inputs assumed for the Mu-Law algorithm include cost of patient waiting ($0.33/minute), clinic overtime cost ($800/hour), revenue ($100/patient), number of slots (30), and slot length

(15 minutes). These inputs should be adjusted to appropriate values for the given clinic setting. In addition, the service time distribution was assumed to be Lognormal (μ=15 min., σ = 5 min.) based on the work by Cayirli et al.[37]

In the Mu-Law method, the schedule for each physician for a particular day is generated using the estimated no-show probability for each patient as they call-in requesting an appointment. The no-show probability for each patient is obtained from the logistic regression model described in the previous section. For each possible slot assignment the expected profit (expected revenue minus expected cost due to patient waiting time and overtime) is estimated and the patient is assigned the appointment slot which gives the maximum profit based on the state of the existing schedule. If the expected profit decreases when the patient is assigned the best slot for that day then the patient is scheduled for another day. The Mu-Law method books until the schedule is saturated, that is, until the addition of one more patient increases expected marginal costs more than expected marginal revenues.

The Mu-Law method might overbook some slots or leave some slots unassigned. The nature of the exact schedule created depends not only on the inputs listed above but also on the sequence in which patients call for appointments. Figure 2 provides an example of a daily schedule of 30 patients scheduled using the current one patient per slot method and using the Mu-Law method. The schedule consists of thirty 15-minute slots. In the figure, patients are labeled according to the order that they called in for an appointment. For the current method, there are more gaps in the schedule that actually occurred (realized schedule) due to patients no-showing to their appointment. For the Mu-Law method there are fewer gaps in the realized schedule because some slots were overbooked. Notice that when the Mu-Law method was used, twice as many (6) of the no-shows occurred from patients that were in overbooked slots compared with (3) no-shows from the normally booked slots.

For actual implementation in a clinic, estimation of no-show probabilities and the Mu-Law scheduling algorithm would have to be incorporated into the clinic scheduling software by software developers.

Results

Results of No-Show Modeling

Results of Model Development The bivariate tests reveal that younger, non-married patients and those with fewer medical costs covered by the VA were more likely to no-show (Table 1). Patients living within 6 miles of the VA had a no-show percent of 21.1%, while those living 7-90 miles and greater than 90 miles away had no-show percents of 12% and 35.3%, respectively. Appointments with a lead time of more than two weeks were more likely to no-show as were appointments scheduled in the winter. Patients with less than four prior visits were more likely to no-show, while patients with diabetes, cardiac conditions, congestive heart failure, chronic obstructive pulmonary disease, or co-morbidities were less likely to no-show. Patients with depression were more likely to no-show as were those with drug dependencies. Finally, patients more likely to no-show included those with fewer days since their last appointment, more hospital admissions, and a higher prior no-show rate.

Stepwise regression using both forward selection and backward elimination resulted in the same final model. The reduced model had a C statistic value of 0.82, which represents the area under the receiver operating characteristic (ROC) curve. In addition, the Hosmer-Lemeshow test, which divides subjects into deciles based on their predicted probabilities and computes a chi-square from observed and expected frequencies, revealed adequate goodness-of-fit (p-value = .26). In other words, the difference between observed and expected frequencies was not significant. The odds ratios and 95% confidence intervals from the final model are given in Table 2. An odds ratio is the odds of an event occurring in one group vs. the odds of the event occurring in another group. In the logistic regression setting, the groups are usually defined by two levels of a covariate and we assume the other covariates are fixed. Thus , for example, if we interpret the first odds ratio given in Table 2, a patient is 4.57 times more likely to no-show to an appointment if they are $\leq$ 50 years old than if they are older than 70. An odds ratio of 1 would mean the odds of no-showing is the same for both groups compared.

From Table 2, the independent risk factors for no-show include younger age, not being married, winter, number of hospital admissions, appointment scheduled more than two weeks in advance, less days since last scheduled appointment, traveling more than 90 miles, less costs covered by the VA, and not having a cardiac condition. The most important factors are the patient's prior no-show rate and number of previously scheduled visits.

The odds ratios for prior no-show rate and prior number of scheduled visits are not reported since the interaction between these two variables is included in the model. The interaction exists because the prior no-show rate depends on how many previous scheduled visits the patient has had. This interaction was explored by estimating the odds ratio and 95% confidence interval for prior no-show rate after fitting the logistic regression model separately for patients with 1-3 previous visits, 4-6 previous visits, and > 6 visits. An increase in the prior no-show percent by 10% increases the odds of no-show by 1.2 [95% CI, 1.1-1.2] for patients with 1-3 previous visits, 1.5 [95% CI, 1.3-1.6] for patients with 4-6 previous visits, and 1.4 [95% CI, 1.3-1.6] for patients with > 6 visits.

In Figure 3, the distribution of estimated probabilities for the validation cohort is given. The distribution is right-skewed with approximately half of the patients having a no-show probability of less than or equal to 10% and eighty percent of patients having a probability less than or equal to 25%. The overall no-show rate is approximately 15%.

Results of Monte Carlo Simulation to Validate Predictive Model When 1000 samples of size 30 (the VA daily schedule size) are drawn from the validation cohort, the expected number of daily no-shows estimated from the model was within 1 of the actual number 42% of the time and within 2 of the actual number 73% of the time.

Results of Appointment Scheduling Using No-Show Probabilities

Figure 4, Panel A and B present results for physician utilization and overtime. Note that each graphic in the figure provides the distribution of the performance measure with respect to the percent of clinic days. For physician utilization, for example, we see that under Mu-Law, 82% of clinic days have physician utilization exceeding 86%, whereas under One/slot, 19% of clinic days have physician utilization exceeding 86%. Further, under Mu-Law, 71% of days have no overtime and only 6% have overtime exceeding 14 minutes. In contrast, under One/slot, approximately 40% of days have no overtime with about 13% of days exceeding 14 minutes. Overall averages indicate that Mu-Law achieves 13% higher physician utilization and 50% less clinic overtime (see Table 3).

Mu-Law overbooks some slots on 83% of clinic days and under-books the schedule on about 10% of clinic days. This is due to the unique sequence of no-show probabilities that it observes in a call-in session. If a sequence of patients with low no-show probabilities call-in, fewer patients will be scheduled than if a sequence of patient with high no-show probability call-in. Figure 4, Panel C and D present distributions for patients served and patient waiting time. Note that the number of patients served under Mu-Law exceeds the number served under One/slot on about 67% of days, with more than 30 patients arriving on about 20% of clinic days (Figure 4, panel C). Overall, the number of patients served is up by approximately 12%, or about 3 patients per day for each physician (see Table 3).

Patient waiting increases under Mu-Law (Figure 4, panel D). However, average waiting time is still less than 15 minutes on approximately 80% of clinic days and is less than 30 on 99% of clinic days. Whether this increased waiting time is acceptable for achieving the improvements discussed above is a question for each clinic to decide. If not, the cost for patient waiting that the clinic uses in the scheduling model can be adjusted. Results of the scheduling algorithm if patient waiting time cost is increased are also reported in Table 3. The scheduling algorithm still performs better than the One/slot method for all performance measures with the exception of waiting time which only increases from an average of 3.4 to 7.6 minutes.

Discussion

This study demonstrated that a statistical model can be developed to describe patients' probabilities of no-showing to their next medical appointment and that these probabilities can be used in an advanced scheduling method to optimize the number of patients served and utilization of physician resources while simultaneously minimizing physician overtime. Increasing clinic efficiency benefits patients because it increases access to care for patients. Furthermore, increasing clinic efficiency can improve clinic revenues which in turn can benefit patients by positively impacting clinic resources.

Naïve overbooking is commonly used in clinic settings to address inefficient use of clinic resources associated with patients not showing to their scheduled appointments. Naïve overbooking is considered naïve because it schedules more than one patient in specific slots without regard to the probability that the patients who are double booked for that slot will not show. Consequences of naïve overbooking include increases in patient waiting times and clinic overtime.[2] In contrast, the scheduling algorithm used in this study uses the patient's no-show probability to determine the optimal way to schedule each successive patient based on the cost of patient wait time, physician idle time, and clinic overtime. Typically, this scheduling algorithm results in multiple booking for those slots that already include patients with a high no-show probability. Specifically, the Mu-Law allows 12% more patients to be served than the current one patient per slot method without increasing the average number of minutes of overtime or the percent of days in which overtime is expected.

Few prior studies have considered patient characteristics in their methods for scheduling appointments and those studies did not incorporate optimization models used in advanced clinic scheduling. For example, one study proposed booking patients until the expected number of arrivals reached the number of appointment slots available for the day.[16] They estimated the expected number of arrivals based on no-show probabilities calculated for a few specific groups (e.g. gender, age (≤14, >14), and number of previous appointments). The model developed here was more comprehensive, including patients' demographic, prior appointment history, diagnoses, insurance and travel time characteristics as well as season. The scheduling model used in this study does not use these no-show probabilities to limit patients' access to appointments, but rather uses them to determine how to optimally schedule patients so as to reduce physician idle time and clinic overtime.

Although the proposed methodology for scheduling is widely applicable, there were limitations to this study. This study includes only patients from a mid-western VA medical center. Thus, this statistical model pertains to a group of patients that are mostly older (77% are older than 50 years old), male, with lower incomes (typically, 70% with annual incomes of less than $20,000 annually).[38] Additionally, we could not determine the diagnoses specific to the visit. Instead, diagnoses that described the patient's most current state of health were used. Future studies should consider whether the reason for the visit or the diagnosis associated with the visit improve prediction of no-show status.

Even though the model developed for this study to determine patients' no show probabilities is likely generalizable only to VA clinic patients, the methods used to develop the model may be generalizable to any clinic for which patient scheduling and billing data are electronically available. Given adequate electronic information about patient and appointment characteristics, we expect that models developed in other clinics would perform as well as the model developed in this study. The scheduling packages that medical clinics currently use do not have these more advanced techniques, although they could be easily implemented. The most apparent reason for this is that too few medical clinics are aware of these capabilities and thus they are not often requested by purchasers of scheduling software.

We performed a cost-benefit analysis for the implementation of proposed methods into an existing patient scheduling software and electronic medical record system. The benefits are the increase in expected number of patients seen and the decrease in overtime. The costs are the software development, customization and training costs. Software development cost includes coding of the algorithms, and integration with the existing scheduling system and database. Customization is necessary to develop a no-show prediction model specific to the clinic's patient population. The waiting and overtime cost estimation is important because of staff and provider preferences. Training of the scheduler is required to explain the importance of scheduling patients to the best available slots.

We assume the benefits occur monthly and the costs are one-time costs at the beginning. The following cost-benefit calculations are for a six-provider practice with $100 revenue per patient and $800 overtime cost per hour. When the waiting cost is $0.33/min, the increase in number of patients arriving per day is 3.2 and the decrease in overtime per day is 3 minutes. If there are 20 working days per month, the total expected increase in profit is $38400, which is calculated as 3.2 patients/provider day * $100 / patient * 20 days * 6 providers = $38400/month. The total expected decrease in overtime cost is $4800/month. The time required for software development is estimated as 160 hours. If the cost per hour is $150, then the total development cost is $24000. The time required for customization of the cost is 160 hours with a total cost of $24000. The training time is estimated as 4 hours. The total implementation cost is $48000. The net present value of implementation of the proposed methods is calculated as

$$NPV = Totalcost + \sum_{t=1}^{T} \frac{Totalbenefit}{(1+i)^{t/12}}$$

where i is the annual interest rate and t is the time that the benefit will occur (t=2 means 2 months after the implementation). If we assume an annual interest rate of 10% (i=0.1), the net present value of implementing the proposed scheduling algorithm will be -$5741 at the end of month 1 and $36777 at the end of month 2. The breakeven point is the time at which NPV is greater than or equal to zero. Thus the clinic starts making a profit at the end of two months following implementation.

In summary, prior research on no-shows and clinic scheduling have generally been presented in the medical literature or in the engineering literature. Studies presented in the engineering literature typically discuss the advantages of advanced scheduling models without incorporating patient information that might affect model performance. Studies presented in the medical literature typically considered patient characteristics associated with no-showing, but did not consider how this information might be considered in advanced scheduling models. This study combined methods from both lines of research and revealed that advanced scheduling methods that consider individual patient probabilities can improve clinic efficiency without limiting access to care by patients who are at high risk for not showing to their next medical appointment.

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Figure legends:

Figure 1: Flowchart of methodology used to develop (bivariate tests and logistic regression) and validate (Monte Carlo simulation and appointment scheduling) no-show model in scheduling.

Figure 2: Example of a daily schedule created using the One-Slot method that represents current practice and using our proposed Mu-Law method that considers no-show probabilities and overbooking. For each method, the realized schedule represents the schedule with service times and actual patient arrivals. Patients are labeled in the order that they called in for an appointment. If a scheduled patient number is missing in the realized schedule then that patient no-showed to their appointment.

Figure 3: Histogram of the estimated no-show probabilities for the validation cohort obtained from the logistic regression model created with the development cohort. As marked with dashed lines, approximately half of the patients in the validation cohort have a no-show probability of 0.1 or less and approximately 80% of the patients have a no-show probability of 0.25 or less.

Figure 4: Panel A and B: Distributions for physician utilization and overtime, Panel C and D: Distributions for patients served and waiting time. Each figure provides the distribution of the performance measure with respect to the percent of clinic days. For example, in Panel A we see that under Mu-Law, 82% of clinic days have physician utilization exceeding 86%, whereas under One/slot, 19% of clinic days have physician utilization exceeding 86%.

Table 1: Patient and appointment characteristics by no-show status for development cohort

N = 3,484		Last Appointment No-show Yes	No	
Demographic		**N (%)**	**N (%)**	**p-value***
Age (years)	≤50	249 (31.4%)	543 (68.6%)	< .0001
	51-60	169 (17.2%)	816 (82.8%)	
	61-70	62 (9.4%)	598 (90.6%)	
	>70	56 (5.3%)	991 (94.7%)	
Marital Status	Married	183 (9.5%)	1739 (90.5%)	< .0001
	Single/Widowed/Divorced	352 (22.7%)	1202 (77.3%)	
Percent of Costs Covered by VA	< 20%	422 (16.4%)	2157 (83.6%)	.016
	20-60%	84 (13.2%)	553 (86.8%)	
	>60%	29 (11.2%)	231 (88.8%)	
Insurance	Medicare or Private	347 (16.0%)	1828 (84.0%)	.233
	Other Insurance	188 (14.5%)	1113 (85.5%)	
Distance to VA	≤ 6 miles	183 (21.1%)	684 (78.9%)	< .0001
	7-90 miles	297 (12.0%)	2172 (88.0%)	
	> 90 miles	48 (35.3%)	88 (64.7%)	
Appointment		**N (%)**	**N (%)**	**p-value***
Day of Week	Monday	98 (14.4%)	581 (85.6%)	.305
	Tuesday	123 (14.4%)	734 (85.6%)	
	Wednesday	62 (14.4%)	369 (85.6%)	
	Thursday	117 (15.6%)	634 (84.4%)	
	Friday	136 (17.8%)	630 (82.2%)	
AM appointment	Yes	270 (15.2%)	1507 (84.4%)	.751
	No	266 (15.6%)	1441 (84.8%)	
Scheduled within 14 days	Yes	64 (12.1%)	463 (87.9%)	.025
	No	472 (16.0%)	2485 (84.0%)	
Winter	Yes	154 (24.9%)	464 (75.1%)	< .0001
	No	382 (13.3%)	2484 (86.7%)	
Clinical Characteristics		**N (%)**	**N (%)**	**p-value***
Charlson Index	0	372 (18.1%)	1682 (81.9%)	<.0001
	1	101 (12.1%)	732 (87.9%)	
	≥ 2	63 (10.6%)	534 (89.4%)	
Hospital Admissions	0	400 (14.5%)	2353 (85.5%)	.026
	1	73 (18.0%)	333 (82.0%)	
	≥ 2	63 (19.4%)	262 (80.6%)	
Number of Previous Scheduled Visits	≤ 3	232 (20.6%)	892 (79.4%)	<.0001
	4-6	172 (13.3%)	1118 (86.7%)	
	>6	132 (12.3%)	938 (87.7%)	
Diabetes	Yes	106 (10.8%)	873 (89.2%)	<.0001
	No	430 (17.2%)	2075 (82.8%)	

Cardiac Condition	Yes	72 (7.3%)	909 (92.7%)	<.0001
	No	464 (18.5%)	2039 (81.5%)	
Major Depression	Yes	144 (19.6%)	592 (80.4%)	.0005
	No	392 (14.3%)	2356 (85.7%)	
Stroke or Dementia	Yes	24 (16.1%)	125 (83.9%)	.804
	No	512 (15.4%)	2823 (84.6%)	
Pain	Yes	313 (15.2%)	1744 (84.8%)	.741
	No	223 (15.6%)	1204 (84.4%)	
Congestive Heart Failure	Yes	31 (11.0%)	250 (89.0%)	.028
	No	505 (15.8%)	2698 (84.2%)	
Chronic Obstructive Pulmonary Disease	Yes	109 (13.2%)	719 (86.8%)	.040
	No	427 (16.1%)	2229 (83.9%)	
Drug Dependence	Yes	237 (23.6%)	769 (76.4%)	<.0001
	No	299 (12.1%)	2179 (87.9%)	
Use Narcotics	Yes	201 (16.8%)	994 (83.2%)	.093
	No	334 (14.6%)	1947 (85.4%)	
Continuous Characteristics		**Mean (SD) N = 536**	**Mean (SD) N = 2,948**	**p-value†**
Days since last scheduled visit		154.7 (114.8)	169.6 (106.5)	< .0001
Number of Hospital Admissions		0.6 (1.7)	0.4 (1.1)	.007
Prior No-Show Rate		0.3 (0.3)	0.1 (0.2)	<.0001

*Likelihood Ratio Chi-Square Test, †T-test

Table 2: Odds ratios
Number of scheduled visits = 3,464
Number of no-show visits = 527
Percent No-show = 15.2%

Effect		Odds Ratio	95% Confidence Limits	p-value
Age group	**≤ 50 vs 71+**	4.57	[3.24, 6.54]	<.0001
	51-60 vs 71+	2.55	[1.81, 3.63]	
	61-70 vs 71+	1.61	[1.08, 2.41]	
Married	**Yes vs. No**	0.62	[0.49, 0.78]	<.0001
Winter	**Yes vs. No**	2.14	[1.67, 2.73]	<.0001
Hospital Admissions		1.21	[1.11, 1.31]	<.0001
Scheduled more than 2 wks in advance	**Yes vs. No**	2.68	[1.90, 3.85]	<.0001
Log(Days since last appointment)		0.83	[0.73, 0.95]	.006
Miles travelled	**7-90 mi. vs. ≤ 6 mi.**	0.93	[0.73, 1.18]	<.0001
	> 90 mi. vs. ≤ 6 mi.	3.79	[2.40, 5.95]	
Level of medical costs to VA (0,1,2)		0.77	[0.63, 0.93]	.005
Cardiac Condition	**Yes vs. No**	0.54	[0.39, 0.74]	<0.0001

*Profile likelihood confidence intervals and Likelihood Ratio Chi-Square tests are reported. Main effects of prior cumulative no-show rate and cumulative number of visits (≤ 3, 4-6, >6) have p-values of <.0001 and their interaction has p-value of .0001.

Table 3: Performance measures for two scheduling methods

Average Performance Measures	One/slot	Mu-Law	
Cost of Patient Waiting		**$0.33/min.**	**$0.49/min.**
Patients scheduled per day	30	32.5	32.5
Patients arriving per day	25.1	28.3	26.7
Patient waiting time, minutes	3.4	9.9	7.6
Physician utilization (%)	78	91	87
Physician idle time per day, minutes	79.6	37.6	60.2
Overtime per day, minutes*	5.7	2.7	0.9
Proportion of days with overtime	0.60	0.29	0.13

*Includes days with zero overtime