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Modeling Patient No-Show History and Predicting Future Outpatient Appointment Behavior in the Veterans Health Administration

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ABSTRACT Background: Missed appointments reduce the efficiency of the health care system and negatively impact access to care for all patients. Identifying patients at risk for missing an appointment could help health care systems and providers better target interventions to reduce patient no-shows. Objectives: Our aim was to develop and test a predictive model that identifies patients that have a high probability of missing their outpatient appointments. Methods: Demographic information, appointment characteristics, and attendance history were drawn from the existing data sets from four Veterans Affairs health care facilities within six separate service areas. Past attendance behavior was modeled using an empirical Markov model based on up to 10 previous appointments. Using logistic regression, we developed 24 unique predictive models. We implemented the models and tested an intervention strategy using live reminder calls placed 24, 48, and 72 hours ahead of time. The pilot study targeted 1,754 high-risk patients, whose probability of missing an appointment was predicted to be at least 0.2. Results: Our results indicate that three variables were consistently related to a patient's no-show probability in all 24 models: past attendance behavior, the age of the appointment, and having multiple appointments scheduled on that day. After the intervention was implemented, the no-show rate in the pilot group was reduced from the expected value of 35% to 12.16% (p value < 0.0001). Conclusions: The predictive model accurately identified patients who were more likely to miss their appointments. Applying the model in practice enables clinics to apply more intensive intervention measures to high-risk patients.

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INTRODUCTION

Incomplete appointments, or patient no-shows, are scheduled appointments that patients either do not keep or do not cancel in time for another patient to be scheduled as a replacement.[1] Documented rates of incomplete appointments vary among health care systems and clinical settings.[2,3] In primary care clinics, no-show rates have been shown to range from 15% to 30%.[4,5] In the most extreme cases, the no-show rates have been reported to be as high as 50% in a primary care clinic and 60% in mental health clinics.[6,7] The Veterans Health Administration (VHA) reported that 18% of the scheduled outpatient appointments for fiscal year (FY) 2008 were not completed, estimating the total cost of such appointments at $564 million annually.[8]

Missed appointments create major dilemmas for health care systems and have a negative impact on patient care, by causing scheduling and operational difficulties for clinics,[9] diminished productivity,[10] reduced access to adequate health care for patients, and disrupted effective disease management.[11] The existing literature suggests that patient nonattendance might be caused by forgetting the scheduled appointments, and that no-show rates may be reduced by using patient reminders, such as phone calls, mailings, and text messages.[12–17] Studies identifying predictors of appointment no-shows may allow researchers and clinicians to improve clinic performance and quality of care.[3,10,18–22] Specific interventions then can be tailored to particular health care clinics (e.g., community clinic, family practice, and large teaching hospital), characteristics of patients (e.g., urban youth, advanced cancer patients, homeless veterans, or persons who are human immunodeficiency virus positive), or types of appointments (e.g., primary care or mental health support) to improve the efficiency of the schedule.[23–27] For example, forecasting patient attendance may help minimize backlogs in scheduling new appointments if a clinic uses reminder calls or text messages to reduce no-shows,[16,28,29] or if a selective overbooking strategy is implemented.[30–32]

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In an effort to identify patients who might benefit from such interventions, we developed a predictive model (Fig. 1) that uses logistic regression to predict a patient's probability of no-show, based on patient demographic characteristics, characteristics of the appointment, and the patient's past appointment-keeping behavior. The predictive model was then used to develop an intervention to target patients with a high risk of no-showing, to increase the chance that the appointment will actually be completed.

METHODS

Predictive Model Data Description

We were granted access to de-identified administrative data, related to outpatient appointments, from the Veteran Affairs (VA) Corporate Data Warehouse, for appointments that were scheduled to occur between October 1, 2005, (FY 2006) and September 30, 2012 (FY 2012). Our data set included patient records from all six service areas of the VHA outpatient clinics: primary care, mental health, specialty medicine, rehabilitation, surgery, and other.

The data were divided into two sets: the training, or model development, set and the testing, or validation, set. The training set included 3,387,645 appointment records. They were collected from records from FY 2010 and FY 2011 and covered four geographically diverse, urban VA health care facilities located in: Houston, Pittsburgh, San Diego, and Tampa. The facilities in those particular cities were chosen because of their high rate of use and because they allowed us to explore the effects of varying geographical differences. Note that appointments from FY 2006 to FY 2009 were used exclusively to generate past historical attendance data for all patients included in the training set.

The testing set included 18,163,927 appointment records. They were collected from 130 VA health care facilities representing 4 months of national data (July 2011, October 2011, January 2012, and April 2012).

Predictive Model Development

We restricted our analyses to modeling techniques that provide probability estimates, such as logistic regression, tree models, or neural nets.[33–35] Our goal was to create a model that would actually be used within the VHA system. Logistic regression was adopted as a modeling technique because its coefficients can easily be interpreted and because the model could be implemented in an Excel routine.[36] We used forward stepwise selection based on the likelihood ratio to

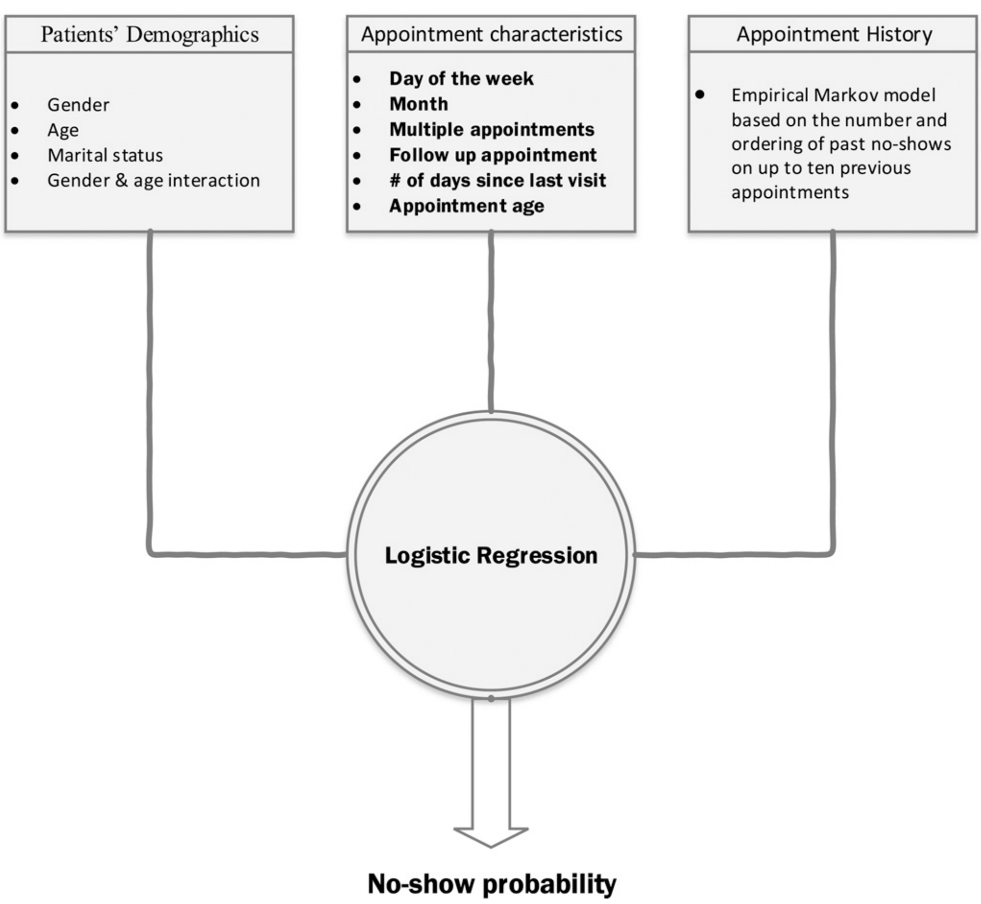

FIGURE 1. Schematic representation of the prediction model.

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choose the variables in the model, with the p value to enter set at 0.05 and the p value for removal set at 0.10.

Our technique of modeling also included accounting for the effects of geographical and service line differences, by splitting the data based on the four facility locations and the six VA service area designations into 24 separate models. Analyses and modeling were conducted in SPSS 21 (IBM, Armonk, New York).

Model Variables

The dependent binary variable was whether the appointment was completed or not (0 = completed appointments, 1 = incomplete appointment). We selected 49 potential independent variables. Independent variables included 26 variables describing patients' demographics, 22 variables describing appointment characteristics, and one variable accounting for patient appointment history (Table I). Our selection was guided by previous studies of no-show outcome models developed by other researchers, as well as by limitations commonly faced in data mining, such as the type of information available.[35,37–39]

Demographic variables included: age (totaling 11 binary variables, representing a patient's age, grouped in 5-year increments, starting at 25, using a thermometer coding, gender (coded as a single binary variable, where female was the base case), marital status (coded as three binary variables: married, never married, and uncoupled, with unknown being the base case). Note that the uncoupled variable for marital status refers to the group of patients that were once married and, therefore, may still have a support system that was in place when they were married; thus, exhibiting different behavioral tendencies than the never married group. Because previous research has shown that age and gender interact,[21] we conducted a preliminary analysis for the significance of an interaction term between age and gender. Using multifactor analysis of variance, we found the interaction term to be significant at the $\alpha = 0.05$ level for all 24 combinations of city and service. Therefore, we created the variable that represents the interaction term or the relationship between age and gender (this created total of 11 variables, coded as M**, where M represents a male patient and ** stands for the upper range of the age group in interval of 5 years, capped at 75).

Variables describing appointment characteristics included day of the week (coded as six binary variables, with Saturday and Sunday aggregated together), month of the years (totaling 12 binary variables), multiple appointments per day, follow-up appointment, number of days since last visit and appointment age.

We modeled only advance appointments (i.e., those made no later than the day before the scheduled date of the appointment), because same day appointments have a very high attendance rate, and it was unlikely that reminder strategies would be useful for them. Prior literature indicates that there is a direct relationship between the no-show rate and the indirect wait between when the appointment is made and when it is scheduled to occur, or appointment age.[10,18,20] After empirically plotting noncompletion rates against appointment lead time, we found that the no-show rate appeared to be related to the natural log of the lead time, and that the curve leveled off after around 60 days. Thus, we censored the lead time at 60 days and used its natural log in the model.

One of the primary challenges and contributions of this study is finding the most appropriate way to represent patient appointment attendance history. Unlike commonly used variables that describe appointment attendance history as either a rate, or only consider the outcome of the most recent appointment,[10,30] we decided that the order of successful appointments would provide a better heuristic tool. The patient appointment history variable is the observed proportion of times that a patient will miss the next appointment, based on the sequence of prior attendance. We used a binary representation of a patients' history—with a completed appointment denoted as a 0 and a no-show as a 1—and list a patient's attendance history from left to right starting with the most recent appointment. For example, the sequence 100 indicates a patient had 3 appointments, missed the most recent one, and showed up for the previous 2 appointments.

We calculated the no-show probability by dividing the number of times a sequence is followed by a success, with the total number of times a sequence is observed. The probability that a person with sequence 0110010, no-shows for the next appointment is:

$$\frac{\text{Number of times sequence 10110010 is in the dataset}}{\text{Number of times sequence 10110010 is in the dataset} + \text{Number of times sequence 00110010 is in the dataset}}$$

This method of calculating the past history variable gives us greater insight into how past appointments affect future

TABLE I. Development and Validation Data Sets

Data Set	Model Development, n = 19,814,248		Model Validation, n = 21,929,642	
Purpose	Historial Attendance Data	Training Set	Testing Set 1	Testing Set 2
Time Period	FY 2007–FY 2009	FY 2010–FY 2011	FY2012	July, October 2011–January, April 2012
VA Healthcare Facilities Locations	Houston, Pittsburgh, San Diego, Tampa	Houston, Pittsburgh, San Diego, Tampa	Houston, Pittsburgh, San Diego, Tampa	130 VA Facilities, Nationwide
Number of Records	12,209,652	7,604,596	3,765,715	18,163,927

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appointments. For example, a patient with 10 past appointments and 5 no-shows has a calculated no-show rate of 0.5, when the ordering of the no-shows is not considered. In our dataset, a patient with sequence 0000011111 attended the 5 most recent appointments and has a calculated no-show probability of 0.1968, whereas a patient with historical sequence 1111100000 missed the 5 most recent appointments and has a calculated no-show probability of 0.5465. Thus, these calculated values are able to adjust for the influence of having more recent no-shows.

Calculating the no-show probabilities for past appointment lengths from 0 to 10 results in an empirical up to tenth-order Markov model table that contains a no-show probability for every possible binary sequence (2,048 possible variations). Note that we capped the number of past appointments to include in this variable at 10, because the number of appointments represented in each sequence degraded past this value.[40] Patients with appointment histories of fewer than 10 appointments were modeled with lower order Markov models of the same type.

Pilot Study Design

To test intervention procedures to reduce no-show rates, using our predictive model, among patients who are most likely to miss their appointments, a 3-week pilot study was conducted at the VA Pittsburgh Healthcare System between July 30, 2012, and August 17, 2012.

All patients received regular automated reminder call as standard procedure in the VA. During the pilot study, the probabilities of no-show for patients from all six service lines were calculated using the appropriate models and student interns from the Veterans Engineering Resource Center placed additional live reminder calls to patients whose appointments, at the time of the calls, were recorded as not having been cancelled, and whose predicted risk of no-show was at least 0.20. Patient appointment schedules were retrieved from the national Corporate Data Warehouse each morning and were compiled for the next business day; Saturday and Sunday were aggregated with the Friday appointments. The relevant predictive model was then applied to calculate the probability that a patient would not show up for their appointment. Because our intention was to test for the most effective intervention, in accordance with suggestions from the VHA, live reminder calls were made 24, 48, or 72 hours in advance.

In total, interns placed an additional 1,754 live reminder calls, where 880 were considered successful contacts. A successful contact was defined as one in which the caller spoke with the patient or another adult about the appointment after no more than three attempts. The appointments were further categorized in terms of whether they were completed or not. Table II presents six different categories, combining the VHA's administrative classifications and records, in combination with the data from the call pilot. Specifically, patient canceled before the appointment (PCBA) refers to appointments cancelled during the intervention calls. The VHA classified these appointments as a separate category, not counting them as either no-shows or as completed appointments. All other categories in Table II were derived directly from the VHA records, corresponding to the calls made during the pilot.

RESULTS

Description of the Models

Three variables: the natural log of appointment age, multiple appointments per day, and the empirical Markov model value based on past attendance history, were significant in all 24 models. The first and third variables had positive coefficients in all models, and the second one had negative coefficients (all p values < 0.05).

The patient demographic variables that were significant across the greatest number of models were being married and getting older. As patients get older, the probability that they will miss their appointments decreases and that effect was present in all 24 models. Similarly, patients who were married had a lower probability of missing their appointments, in all but three models (Houston Rehabilitation, San Diego Rehabilitation, and Tampa Other).

TABLE II. Pilot Results by Age Group and Call Ahead Time

	Under 35			35–60			Over 61		
Successfully Called	24 Hours	48 Hours	72 Hours	24 Hours	48 Hours	72 Hours	24 Hours	48 Hours	72 Hours
PCBA Rate (%)	22.97	17.81	20.00	22.09	13.55	18.49	15.79	18.52	17.57
CCBA Rate (%)	4.05	4.11	3.08	3.68	1.29	0.84	1.32	4.94	2.70
PCAA Rate (%)	0.00	0.00	0.00	2.45	2.58	1.68	2.63	1.23	0.00
CCAA Rate (%)	0.00	1.37	0.00	1.23	0.00	0.00	0.00	2.47	1.35
Completed Rate (%)	66.22	69.86	63.08	60.12	67.10	66.39	68.42	65.43	55.41
No-Show Rate (%)	6.76	6.85	13.85	10.43	15.48	12.61	11.84	7.41	22.97
Age/Call Ahead Total	74	73	65	163	155	119	76	81	74
Age Group Total	212			437			231		
NS Rate for (%) Group	8.96			12.81			13.85		

CCAA, clinic cancelled after the appointment; CCBA, clinic canceled before appointment; PCAA, patient canceled after the appointment; PCBA, patient cancelled before the appointment.

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Appointment age always increased the probability of no-show. The coefficients for appointment age ranged from 0.076 to 0.328—Houston Rehabilitation and Pittsburgh Other, respectively—which related to between a 7.8% to 38.7% increase in no-show probability with a unit increase in the natural log of appointment age.

Multiple same-day appointments decreased the probability of a no-show from 51% to 13% across all 24 models, meaning that a patient was more likely to show up when he/she had two or more appointments on the same day. Similarly, if an appointment was a follow-up, it decreased the probability of a no-show in all but three models (Houston Other, San Diego Rehabilitation, and Tampa Other).

Patient appointment history, based on the sequence of the previous attendance, was significant in all models. An increase in the value of the past history variable lead to an increase in the overall no-show probability.

Model Performance

To evaluate model performance, we calculated the area under the curve (AUC), also known as the c-statistic, using the receiver operator characteristic for all models. The average of the areas under all receiver operator characteristic curves was 0.762 for the training dataset, and 0.71291 for the test set. Excluding the four modeling sites, the average AUC was 0.71249. The average AUCs across the six service lines for Houston, Pittsburgh, San Diego, and Tampa, were 0.7094, 0.7143, 0.7017, and 0.717, respectively.

Model Implementation

The staff of the call pilot reached a total of 880 out of 1,754 patients (successful contact in 50.17% of the cases). The overall patient no-show rate for successfully contacted patients was 12.16%. In contrast, for the 874 patients with whom there was no successful contact 471 did not complete their appointments (53.8%). The no-show rate was the lowest for the group that received reminder calls 24 hours in advance (9.9%) and the highest for the group that received reminder calls 72 hours in advance (15.89%). Conversely, the highest PCBA rate was the greatest for the group that received an intervention call 24 hours ahead of time (20.77%), with the average PCBA rate being as high as 18.41%.

If we look at the results more closely, to account for the effects of the age, we see that timing is of particular importance. In Table II, the results of the pilot are broken down into three age groups and three groups based on the amount of time in advance that the calls were made. The PCBA rate is higher when calling 24 hours ahead.

For patients under 35, similar results were observed when calls were made 24 and 48 hours before the scheduled appointment (6.76% and 6.85%, respectively), and the no-show rate increased when calls were made 72 hours in advance. For patients between 35 and 60 years of age, receiving a reminder call 24 hours in advance showed the best results (10.43%), whereas patients older than 60 years of age had the lowest no-show rates when called 48 hours in advance (7.41%). Interestingly, for patients both younger than 35 and older than 60 years of age, calling 72 hours ahead was the least effective (no-show rates of 13.85% and 22.97%, respectively).

We derived the expected no-show rate using the predictive models for the specific service lines in the VA Pittsburgh Healthcare System. For patients whose predicted probability of no-show was at least 0.2, the expected no-show rate was 35%. After the intervention was implemented, the no-show rate was reduced to 12.16%, a statistically significant decrease ($p < 0.0001$).

DISCUSSION

Creating a model to predict patient behavior has been a focus for researchers interested in improving the quality of patient care and access to medical services. Our results showed that a predictive model can be used across a variety of clinics to predict a patient's future no-show behavior, by incorporating variables such as patient demographics, appointment characteristics, and patient historical appointment-keeping behavior.

We found that the most important indicators of future patient no-show behavior were past appointment history, appointment lead time, and multiple appointments on the same day. All of those variables are readily available in administrative data, and the latter two can be set by health care providers when scheduling future appointments; thus, improving the overall appointment attendance.

Our findings regarding the key indicators are consistent with past research on no-show modeling.[5,18,22] We contribute to the modeling methodology by developing a unique way of thinking about patient attendance history. Our contribution is distinctive in its representation of no-show behavior as we use an empirical probability that accounts for the number and ordering of past no-shows. Such an approach goes beyond simply using a no-show rate.[10] The association between the age of the appointment and no-show probability is intuitive—the shorter the lead time, the more likely a patient is to attend an appointment—and consistent with results found in the literature.[10,18,20,21] We found that there is a positive correlation between having multiple appointments scheduled for the same day and the attendance rates. With one exception that briefly mentions multiple appointments on the same day as possibly decreasing no-shows, we could not find any other studies that incorporate this variable in the analysis.[29] Thus, our model identifies a new factor that influences the probability of a no-show that should be further explored in other clinical settings. Furthermore, clinics outside of the VHA may need to consider adopting the strategy of scheduling multiple appointments on the same day when possible.

In terms of patient characteristics, our findings that older, married patients tend to show more often for their

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appointments corresponds to the existing literature.[10,21] The majority of the existing literature that examines the influences of gender on no-show rates does not find significant differences between males and females.[19,20,22] Our results; however, are consistent with the more recent and growing body of studies that finds that males are less likely to keep their appointments.[21,41]

In addition to developing predictive models that facilitate the identification of patients at higher risk for non-attendance, we also performed a pilot study to test an intervention strategy (such as live reminder calls, 24, 48, and 72 hours in advance) with the goal of reducing no-show rates. The no-show rate was the lowest for the group that received reminder calls 24 hours in advance (9.9%) and the highest for the group that received reminder calls 72 hours in advance (15.89%). The one exception was with patients older than 60 years of age, who were the least likely to miss their appointments when called 48 hours ahead of time (7.41%). This shows not only that targeted intervention strategies can significantly improve no-show rates, but that such strategies have to be tailored more specifically to patients or patient groups.

Additionally, because the PCBA average was 18.41% across all calling groups, representing a large portion of appointments that could be otherwise rescheduled, future research is needed to investigate how to implement reuse of cancelled appointment slots, to reduce the both no-show rates and the amount of time patients wait for their appointments. Although the population of patients in the VHA is likely to be older and more predominantly male than the general population, further research might determine how well our results generalize beyond the VHA.

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