A Predictive Model for Decreasing Clinical No-Show Rates in a Primary Care Setting

M Usman Ahmad
USF MCOM- LVHN Campus, Mohammad.Ahmad@lvhn.org

Angie Zhang
USF MCOM- LVHN Campus, Angie.Zhang@lvhn.org

Rahul Mhaskar MPH, PhD

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A Predictive Model for Decreasing Clinical No-Show Rates in a Primary Care Setting

M. Usman Ahmad, B.A.[1], Angie Zhang, B.A.[1], Rahul Mhaskar, M.P.H., Ph.D.[1,2]

1. Medical Education, University of South Florida (USF) Morsani College of Medicine (MCOM), Tampa, FL
2. Internal Medicine, USF MCOM, Tampa, FL

Lehigh Valley Health Network, Allentown, Pennsylvania

Background

A challenging obstacles to primary care delivery in the United States (US) is patient no-shows or missed appointments.

- No-show rate in can vary from 5.5% to 50%[1-6]
- Loss to revenue from a no show rate of 5.5% was salary of three nursing staff[1]
- Requires tailored prediction tool to target reduction strategies efficiently[5]
- Solutions: phone reminders[7], automated phone reminders[8], text messages[8,9], exit interviews[10], fees[11], overbooking[12-14], predictive modeling[15-20], and predictive modeling with overbooking[21-30]

Problem Statement

The clinical no-show rate is a cause of lost productivity in primary care, predictive models may help reduce the rate.

Methods

An IRB approved study was conducted to retrospectively develop a predictive model and prospectively test the model.

- Staff interviews and process mapping defined the problem.
- Patient visits from 2014-2015 were analyzed with regression using STATA 13
- Variables included month, day, age, gender, race, ethnicity, insurance type, visit type, and number of previous no shows
- A threshold for classifying no shows was determined using a histogram
- The model was tested on patient visits in 2016 with sensitivity, specificity, and receiver operating characteristic (ROC) curve calculated
- The model was used to simulate overbooking by visit day on the prospective sample

Results

6,758 patient visits were analyzed with probit regression.

- Significant variables included: 18 to 25 years of age, 36 to 39 years of age, check up visits, no insurance, and two previous no-show visits.

3,571 patient visits were used to test the model

- Model performed at 47% sensitivity and 79% specificity
- Simulated predictive overbooking resulted in 3.67 vs. 6.87 unused appointments, p<0.000 (mean diff 3.2, 95% CI, 2.9 to 3.5). Visit utilization increased from 69% with normal scheduling to 82% with predictive overbooking.
- The receiver operating characteristic (ROC) curve area under curve (AUC) was 0.72 (95% CI, 0.69 to 0.76) for the model and 0.70 (95% CI, 0.65 to 0.74) for predicted visits.

Table 1: Demographics

Characteristics	Phase 1 (n = 2,946)	Phase 2 (2,209)
Age, years: mean (SD)	51.6 (18.6)	53.2 (18.9)
Sex, male: N (%)	1744 (59.2%)	1317 (59.6%)
Race, N (%)		
White	2677 (90.9%)	1989 (90.0%)
Black	165 (5.6%)	133 (6.0%)
Hispanic	48 (1.6%)	39 (1.8%)
Asian	27 (0.9%)	24 (1.1%)
Other	29 (1.0%)	24 (1.1%)
Ethnicity, Hispanic (%)	65 (2.2%)	48 (2.2%)
Insurance, N (%)		
Medicare	601 (20.4%)	499 (22.6%)
Private Insurance	2213 (75.1%)	1634 (74.0%)
Uninsured	132 (4.5%)	76 (3.4%)

Table 2: Results of Probit Regression Analysis

Month	Beta Coefficient (95% CI)	Significance
No significance		
Day		
No significance		
Age		
18 to 25	0.31 (0.05 to 0.57)	0.019*
36 to 49	0.26 (0.06 to 0.45)	0.012*
Gender		
No significance		
Race		
No significance		
Insurance		
Medicare	-0.3 (-0.6 to -0.01)	0.046*
Private Insurance	-0.27 (-0.51 to -0.03)	0.030*
Uninsured	0 (0 to 0)	Reference
Visit Type		
CU	0.39 (0.23 to 0.56)	0.000*
Previous No Shows		
Twice	0.94 (0.3 to 1.58)	0.004*

CU = Check Up, INJ = Injection, OV = Office Visit, NP= New Patient, Physical = Physical Exam, * = significant at p <0.05
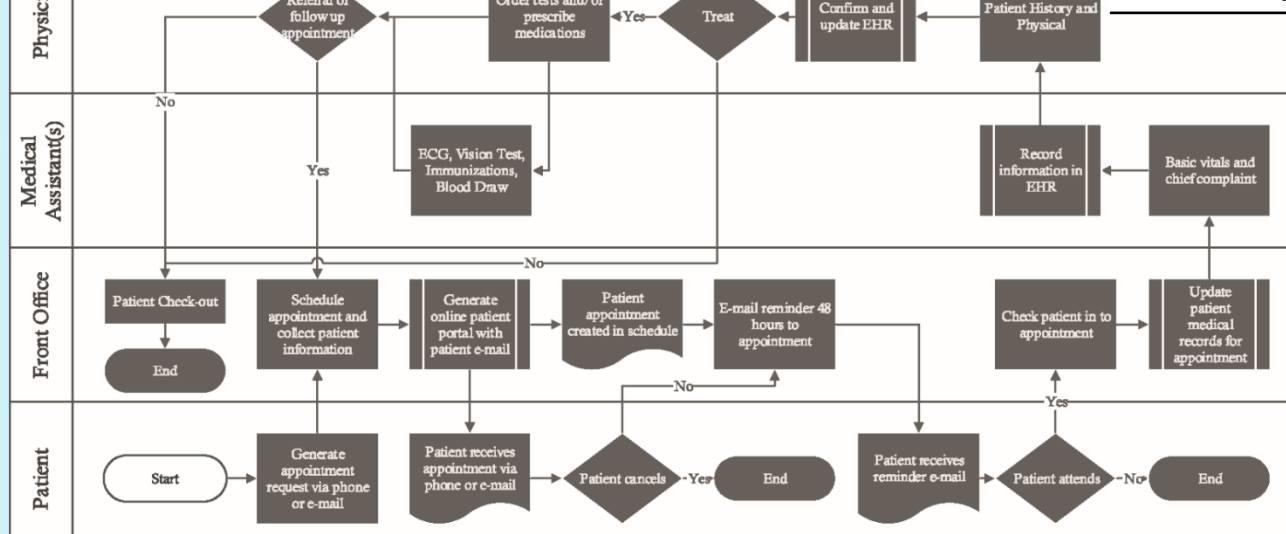
**Figure 1:** A process flow diagram constructed with Microsoft Visio for the single physician office with typical patient flow.

Family Medicine Practice Patient Flow Diagram

Figure 2: a) A histogram plotted using Microsoft Excel with the output of the regression equation for 6,758 patient visits from 2014-2015. Visit status by show and no show is separated to highlight distributional differences. A threshold of 0.16 was chosen to classify a visit as a show or no show for model deployment. b) 251 visit days were analyzed with one excluded as holiday scheduling. The remaining visits, no shows, and overbooked appointments with predictive model were compared to maximum capacity for each visit day. Visit days are displayed as weeks with holiday weeks 23, 28, 29, 37, 48 and 53 excluded to simplify maximum capacity. c) The threshold value of 0.16 is marked on the receiver operating curve (ROC) for the training data in Microsoft Excel. The area under the curve is 0.72 (95% CI, 0.69 to 0.76). d) The threshold value of 0.16 is marked on the receiver operating curve (ROC) for the predicted data. The area under the curve is 0.70 (95% CI, 0.65 to 0.74) in Microsoft Excel.
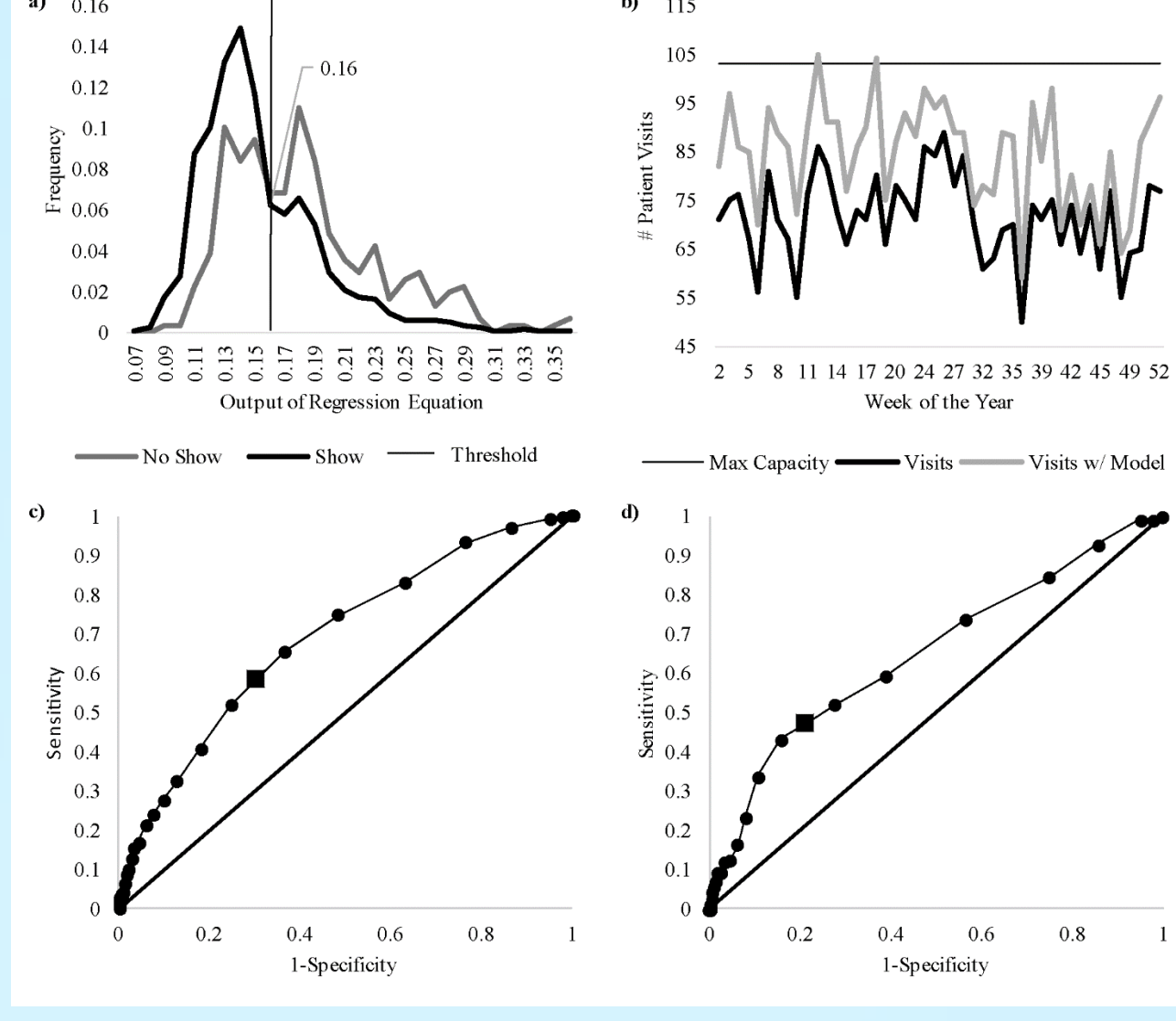
Discussion

Age, visit type, insurance status, and two previous no show visits were significant in our model.

- Previous research is mixed on age and insurance status[6,31]
- No association between no shows and race or gender which conflicts previous research[19,20]
- Predictive modeling with overbooking has not been studied in single physician practices, but is effective[21-30]
- Visits for chronic illness or hospital admissions have higher no show rates[32]
- SELECT: Leadership and knowledge of health systems with technology can improve practice efficiency while emphasizing improved patient care as it relates to chronic illness and hospital follow ups.

Conclusions

It is possible to develop a predictive model for no shows for clinics as small as single physician practices.

- Some significant variables were similar to prior research, however, others differed.
- Predictive modeling in conjunction with overbooking may provide an opportunity to mitigate the effect of no shows.
- SELECT tools would be necessary to balance staff wellness, patient care, and revenue goals

REFERENCES