Department of Industrial and Systems Engineering | System Design Project

Predicting Patient No-Show Rate to Increase Scheduling Efficiency

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Background

One year medical appointments data with an average of 2000 appointments per day were studied. Almost 15% of these patients did not show up for their appointments. High no-show rate interrupts normal clinic operation. More importantly, not coming for appointments may hinder patients' recovery.

Fig 1 gives a breakdown of no-show rates across some frequently visited specialties in 2011. An illustration of the current appointment making practice is shown in Fig 2.

Objective

- Identify potential patterns in patients' no-show behaviour;
- Minimize no-show rate;
- Optimize resource utilization.

Fig 1. No-Show Rate in Selected Specialties

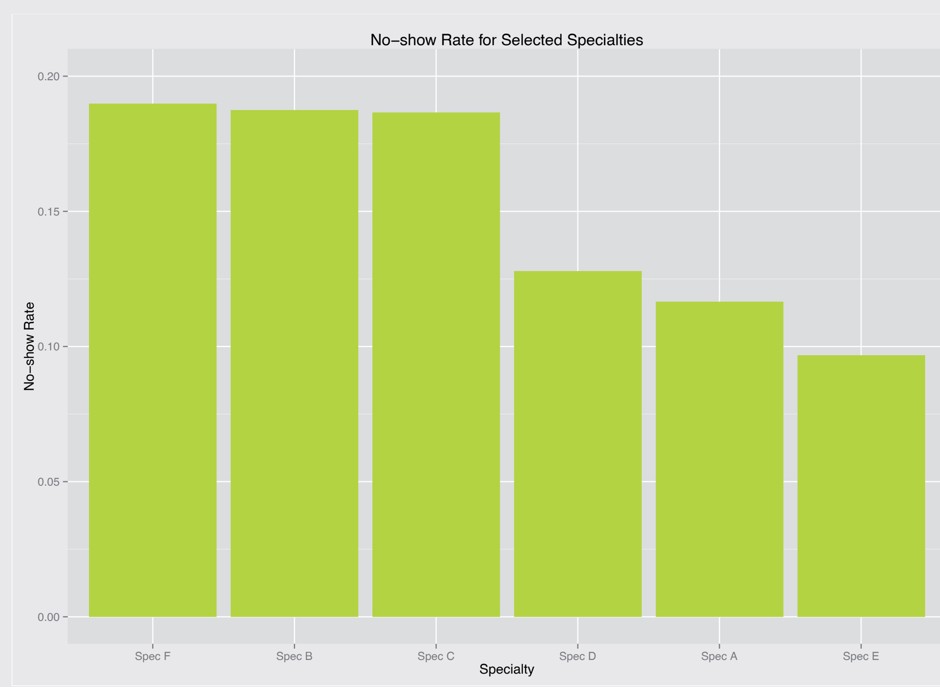
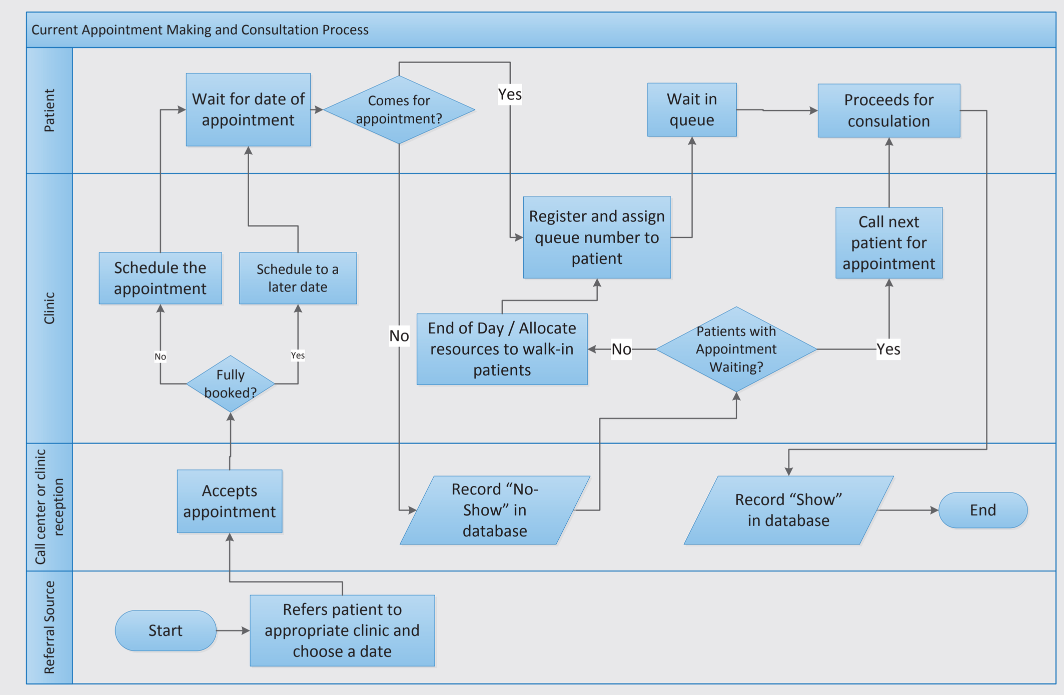


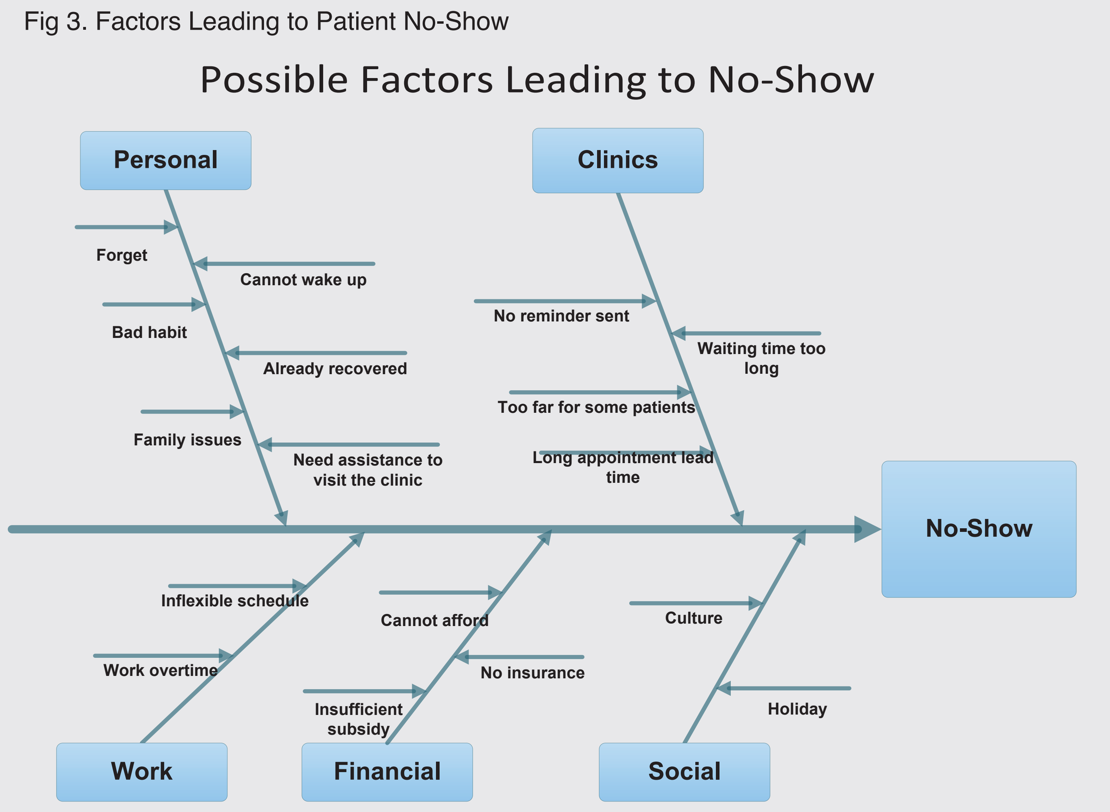
Fig 2. Current Appointment Making Process



Possible Factors

Fig 3 shows the team's initial postulate about possible factors which may influence the no-show behaviour of patients. Patients across different age groups and genders, staying in different regions, of different marital status usually demonstrate different levels of no-show tendency.

Fig 3. Factors Leading to Patient No-Show

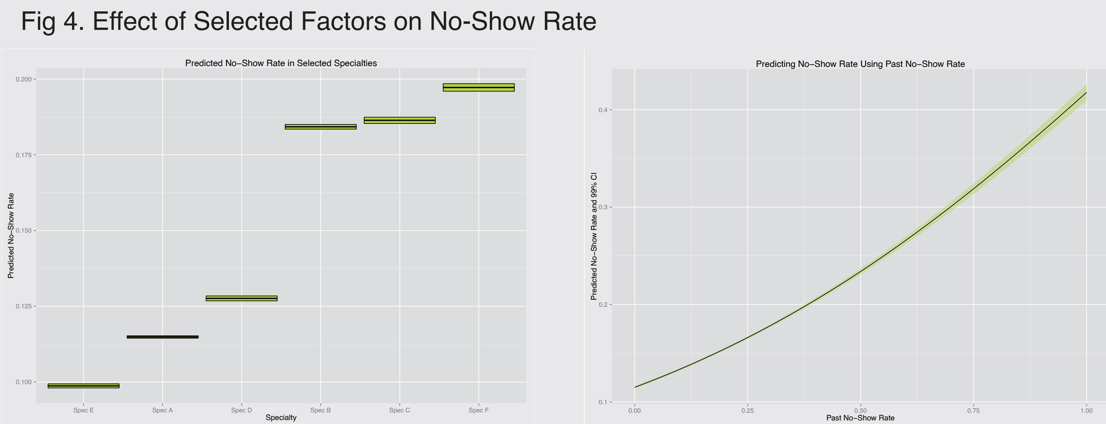


Predictive Model

Jan to Sep 2011 data is used for model building while data from Oct to Dec 2011 is reserved for validation. Two predictive models for patient no-show probability are proposed.

Model 1 uses logistic regression with predictors such as age, gender, distance from clinic, specialty, past no-show rate, referral code and subsidy category. Model chi square = 30968.27 with 88 degrees of freedom and p-value = 0.000. Figure 4 visualises the effect of selected factors on fitted no-show rate. The shaded region represents the 95% confidence interval of mean. Fig 5 and Fig 6 show the effect of combinations of factors.

Fig 4. Effect of Selected Factors on No-Show Rate



Model 2 uses Bayesian inference to update a logistic regression's initial prediction. The prior distribution is assumed to be beta distribution. α increases if a patient fails to show up for one appointment and β increases if he shows up. As seen in Fig 7, the model reacts by increasing a patient's predicted no-show probability if he failed to show up for the last appointment. The opposite happens if he shows up.

Fig 5. Patients between 20-40 years old from A&E Department are more likely to become "no-show" cases

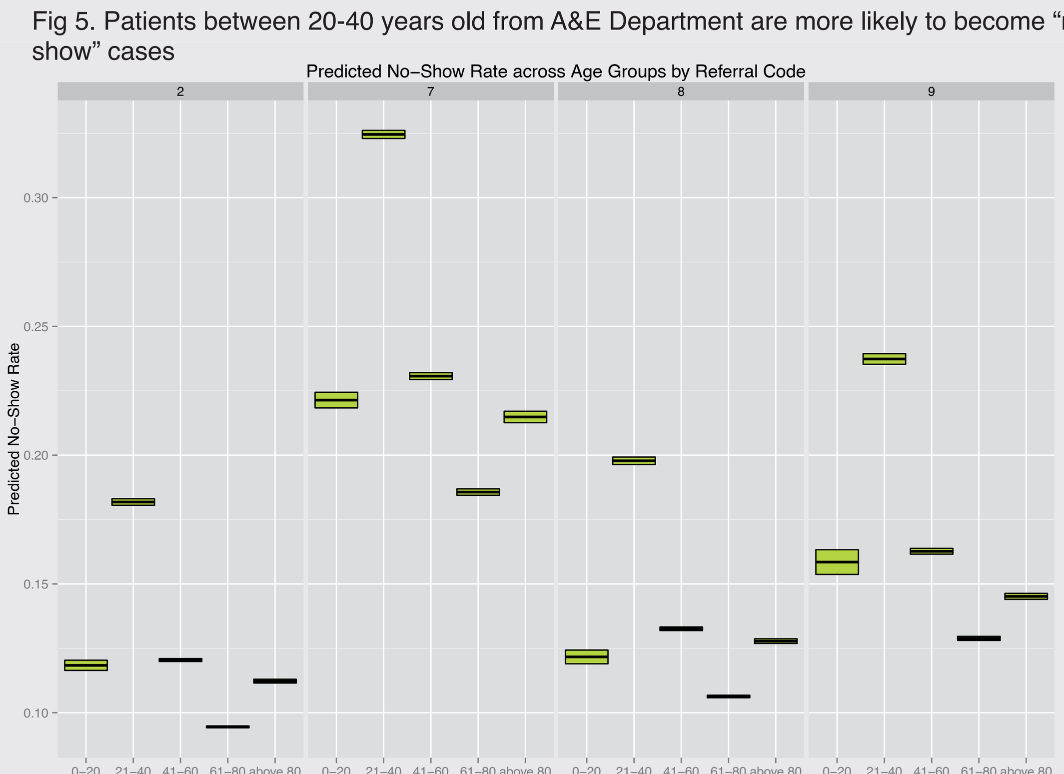


Fig 6. Patients in Specialty F have greater tendency for "no-show" given their past no-show rate

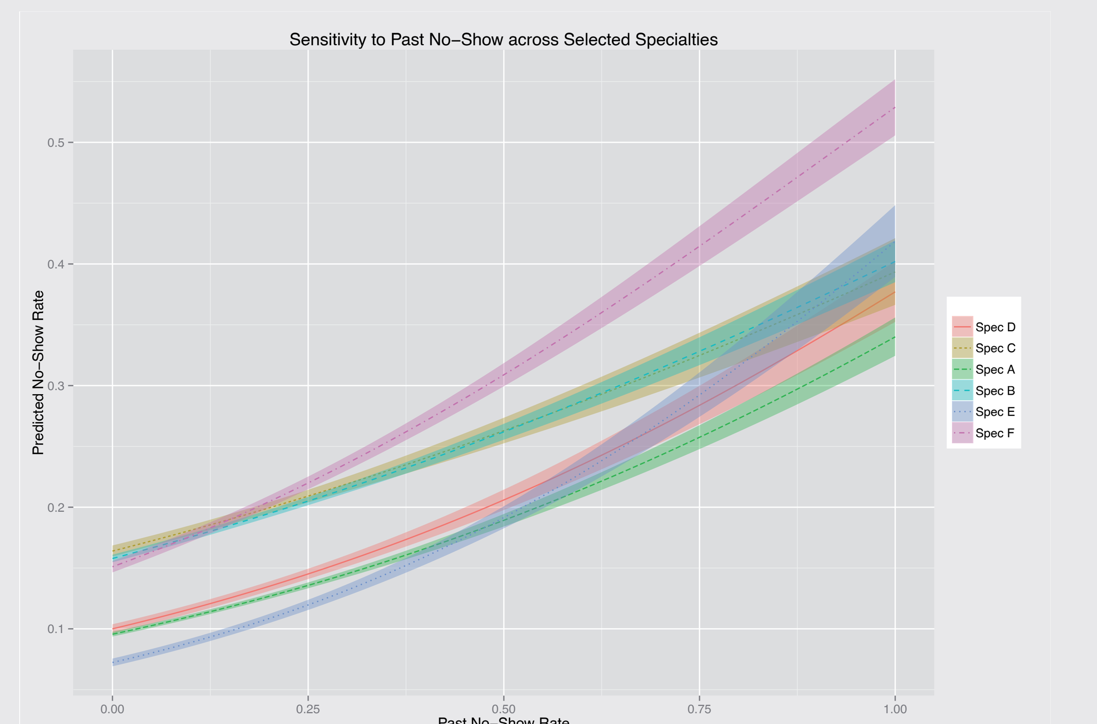
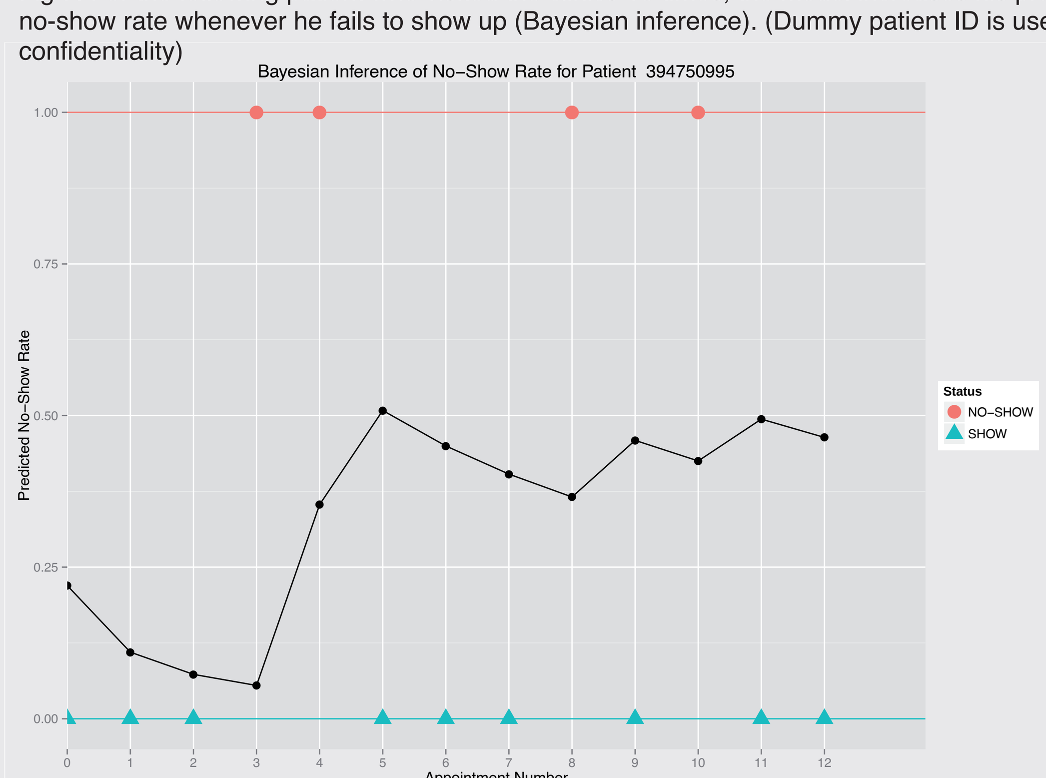


Fig 7. For the following patient who visited the clinics 13 times, the model increases his predicted no-show rate whenever he fails to show up (Bayesian inference). (Dummy patient ID is used for confidentiality)

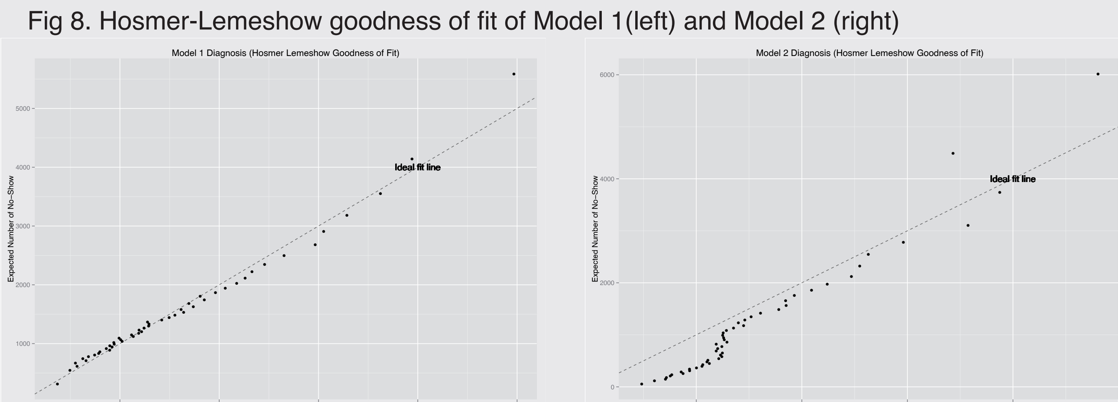


Model Validation

Although Model 2 uses an extra procedure to account for individual patient's no-show behaviour, it is out-performed by Model 1 in terms of Hosmer-Lemeshow goodness of fit. This may be due to the limited time span of available data (1 year). We have therefore decided to use Model 1 for the later part of the study.

Nevertheless, Model 2 can be useful because it has the ability to self-update when longer period of data is accumulated in the future.

Fig 8. Hosmer-Lemeshow goodness of fit of Model 1(left) and Model 2 (right)

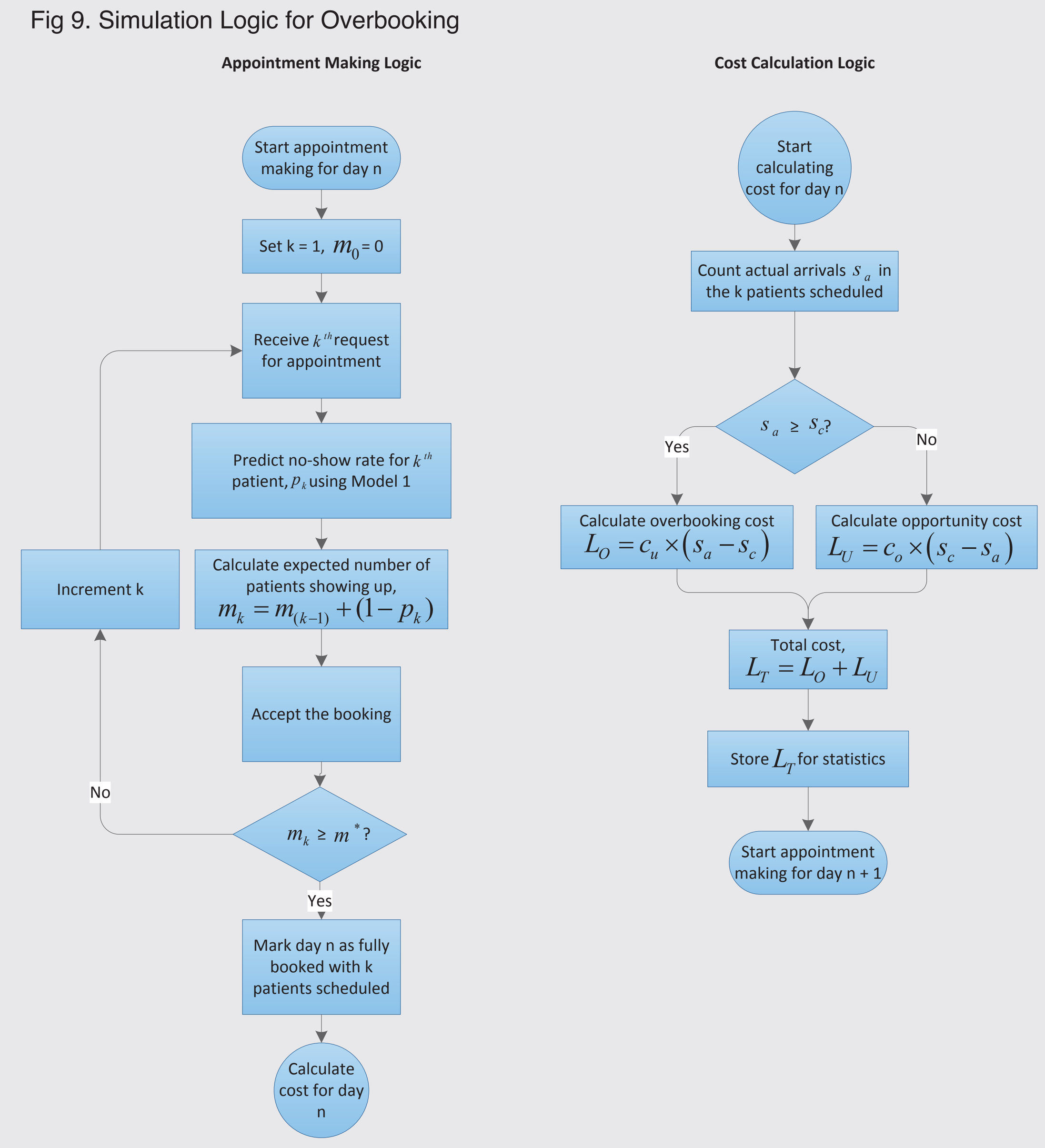


A simulation of 1000 trials was conducted to validate the prediction. 62% of the time, Model 1 predicts the number of no-show within an error of three for every 100 appointments.

Proposed Solution

- A potential way to reduce waste of resources caused by no-show patients is to schedule more patients to the existing timeslots;
- Overbooking cost, c_o in the form of staff overtime and patients waiting is incurred when more than expected number of patients show up; Opportunity cost, c_u in the form of lost consultation fee is incurred when less patients show up than a clinic can handle;
- A modified version of the traditional Single Period Inventory Model is proposed;
- Model 1 is used to calculate the expected number of patients showing up, m_k;
- When m_k as predicted by Model 1 reaches the optimal cut-off point

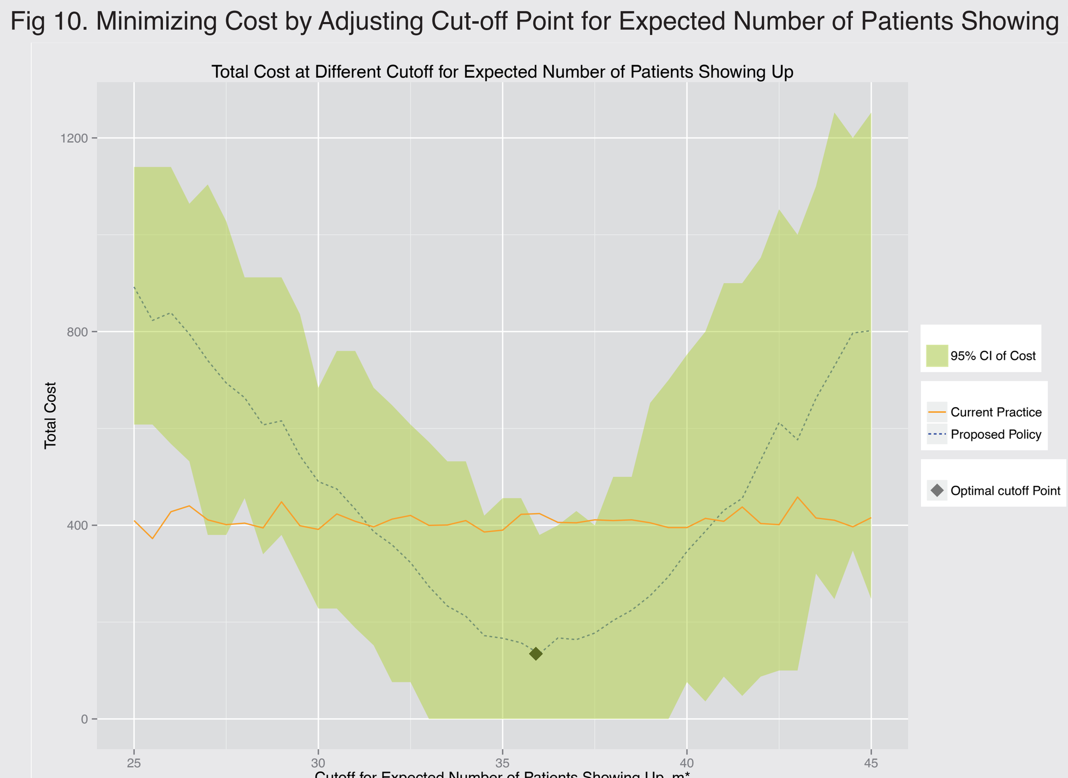
Fig 9. Simulation Logic for Overbooking



m^*, stop the booking and mark the day as fully booked;

- A one-dimensional golden-section search algorithm is used to find the optimal cut-off point m^*;
- Under this policy, the decision variable m^* will be determined as a fixed value. However, the number of patients allowed to make appointments varies. Intuitively, for specialties where no-show rates are higher, more patients will be scheduled for the day. On the other hand, if many scheduled patients have low predicted no-show rate, less patients will be scheduled;

Fig 10. Minimizing Cost by Adjusting Cut-off Point for Expected Number of Patients Showing up



- For the case where daily capacity, s_c = 36, assuming average consultation fee, c_u = \$76 and c_o = overtime pay = \$100, total cost is obtained by the simulation logic illustrated in Fig 9. Total cost is plotted against different levels of m^* in Fig 10;
- As shown in Fig 10, cost saving of \$259/clinic/day can be achieved when the cut-off m^* = 35.9.

Recommendations

- Consider taking into account individual patient's no-show probability when scheduling the appointments. The overbooking policy above illustrates a possible way to reduce opportunity cost due to patient no-show;
- Continue collecting no-show data. We have demonstrated that past no-show record is a good predictor of future no-show probability;
- Consider devoting more resources to SMS and letter reminder systems as they are shown by the statistical model to be more effective compared to electronic medium such as email reminders.