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Effects of clinical characteristics on successful open access scheduling

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Abstract Many outpatient clinics are experimenting with open access scheduling. Under open access, patients see their physicians within a day or two of making their appointment request, and long term patient booking is very limited. The hope is that these short appointment lead times will improve patient access and reduce uncertainty in clinic operations by reducing patient no-shows. Practice shows that successful implementation can be strongly influenced by clinic characteristics, indicating that open access policies must be designed to account for local clinical conditions. The effects of four variables on clinic performance are examined: (1) the fraction of patients being served on open access, (2) the scheduling horizon for patients on longer term appointment scheduling, (3) provider care groups, and (4) overbooking. Discrete event simulation, designed experimentation, and data drawn from an intercity clinic in central Indiana are used to study the effects of these variables on clinic throughput and patient continuity of care. Results show that, if correctly configured, open access can lead to significant improvements in clinic throughput with little sacrifice in continuity of care.

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1 Introduction

Large outpatient healthcare clinics schedule thousands of patient appointments each year. The effectiveness of the scheduling process has a direct and critical impact on clinical resource usage and patient satisfaction. Typically, appointments can be made many months in advance, and when a clinic is working close to capacity, the near term schedule tends to be fully utilized. This limits patient access to care and aggravates the problem of patient no-shows, which refers to those patients who miss their appointments with no forewarning. In some clinics, no-show rates can be as high as 42%, introducing enormous volatility in clinic operations and wasting clinical resources [19]. This is not surprising since, during a long appointment lead time, the patient's needs can change significantly.

To address the issues of timely access and patient no-show, *open access scheduling* is being introduced in clinics throughout the United States. Rather than booking a patient several weeks or months in advance, patients are asked to call for appointments about the time they wish to see their physicians. If appointment slots are available within the next day or two, the calling patient is scheduled. If not, the patient may be asked to call back later. When demand and capacity are properly balanced, open access can help improve patient access to physicians and reduce uncertainty in clinic operations by eliminating no-shows resulting from long appointment lead times [21]. However, when demand and capacity are not properly balanced, having patients call back later leads to an increasing and unstable call rate, unfair access, and high patient dissatisfaction.

Thus, despite its appeal, open access can fail if not customized for the individual clinic's capacity and environment. For example, under open access, patient continuity of care (access to appointments with the patient's regular physician) is much more sensitive to physician work patterns, especially when medical interns and student residents are present. Also, the clinic's patient demographics, its physical location and proximity to public transportation, and its no-show history all can be important in clinical scheduling and operations. Finally, some patients, such as those with chronic disease, may require follow-up appointments. Refusing to book these at the end of the current appointment does not promote patient satisfaction.

The objective of this research is to develop modeling and analysis techniques that help configure open access to a clinic's unique environment, taking into account the variables mentioned above as well as many others. A complete overview of these efforts is documented in [6], which describes the overall modeling framework and implementation approach (see Fig. 1). This framework includes a variety of analytical models for open access configuration decisions and requirements such as (1) modeling patient no-show, (2) finding an optimal mix of open and longer term scheduling slots (see Fig. 2), (3) accommodating schedule backlog during open access implementation, (4) forming provider care groups, (5) modeling patient flow in the clinic, and (6) using overbooking to offset the effect of patient no-show. These models are used to develop an initial configuration, which is then simulated and refined (see Phase I of Fig. 1). The refined configuration is then continually adjusted and refined during Phase II. During this transition period, open access is phased in as schedule backlog is worked down. When the transition to open access is complete, the demand process, patient no-show rates, physician work patterns, and so forth are constantly monitored and the scheduling policies are continuously updated and refined. Eventually, the environment might change so much that the three phase process repeats itself.

This paper describes the simulation component of the framework (see Phase I) and presents the results of a designed experiment in which the effects of clinical characteristics on two clinical performance measures are investigated: continuity of care and clinic throughput. This modeling approach was developed in collaboration with medical partners at a large outpatient general practice clinic, which serves an inner city population and is associated with a major tertiary teaching hospital with over 950 faculty physicians providing care across a wide spectrum of disciplines.

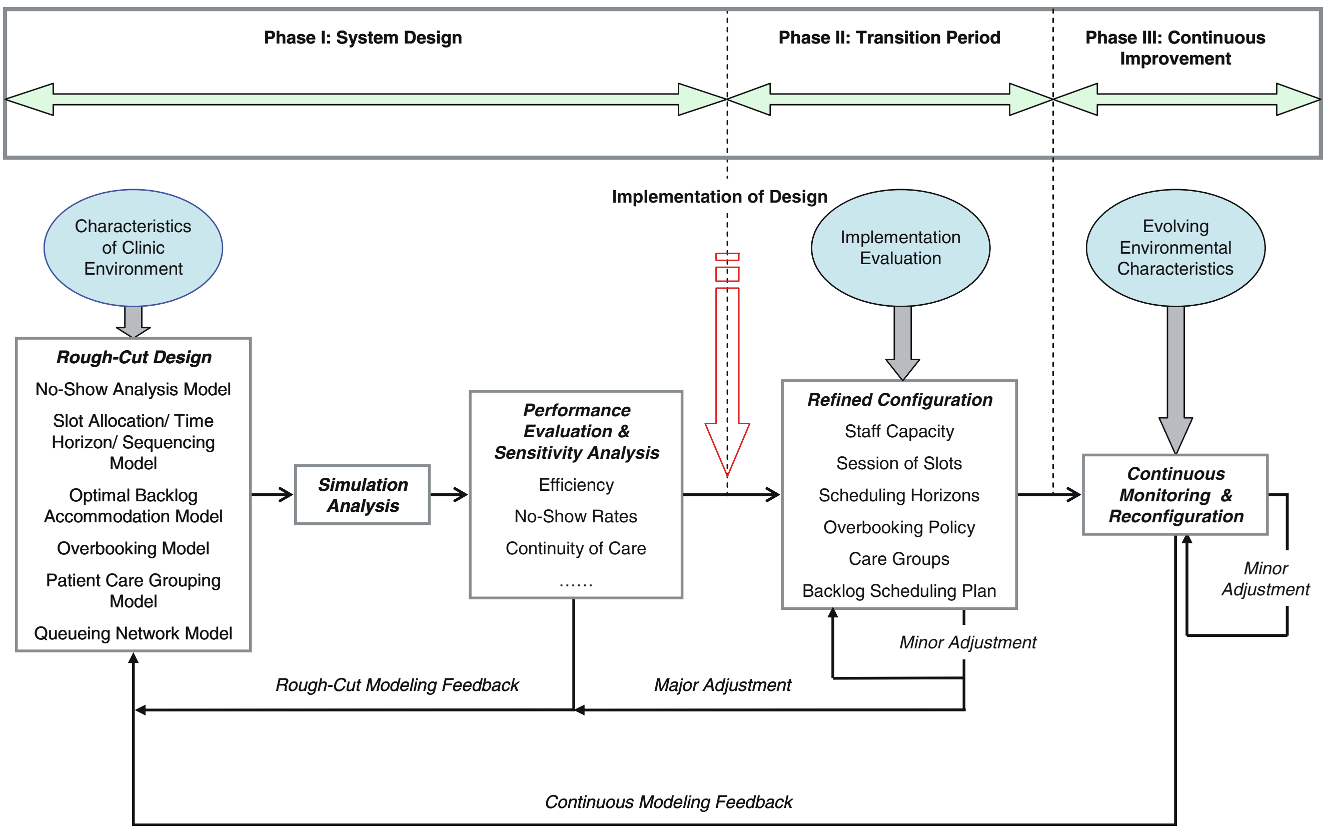

Fig. 1 Framework for configuring open access

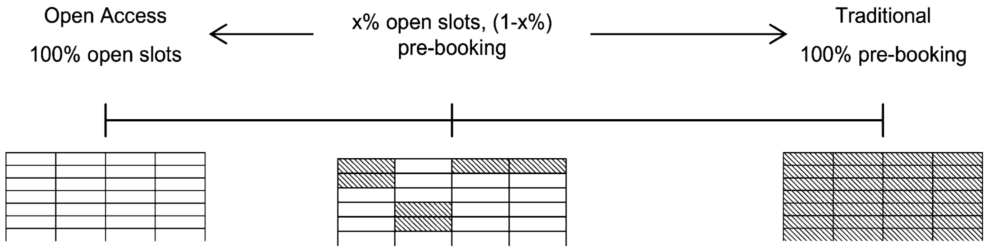

Fig. 2 Mix of open and long term scheduling slots

The contributions of this paper include:

1. A simulation framework that integrates models of the call-in process, patient no-show, and clinic performance;
2. An analysis of the effect of provider care groups on continuity of care and clinic performance;
3. An overbooking approach for improving patient access and an assessment of its effect on continuity of care and clinic performance;
4. An analysis of the effect of the fraction of a clinic's patients using open access.
5. A tentative model for the relationship between appointment lead time and patient no-show, and an illustration of the negative effect of patient no-show on clinic throughput.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review, while Section 3 discusses the methodological approach, which includes steps for (1) identifying modeling objectives, performance measures, and clinical variables, (2) performing data collection and input analysis, and (3) developing and validating the clinic simulator. Section 4 then presents the experimental design, while Section 5 discusses results, which illustrate the effects of clinic characteristics on the two performance measures given above. Finally, Section 6 summarizes and discusses future work.

2 Literature review

This section provides a literature review for patient no-show research and outpatient appointment scheduling. The no-show literature is important since it establishes that no-show prediction models can be successfully developed, but that the significant factors affecting no-show are clinic dependent. The appointment scheduling literature is important as it provides the foundation for analysis of open access as a new scheduling paradigm.

Patient no-show is a chronic problem for outpatient clinics, where no-show rates range from 12 to 42% [19]. No-show patients waste resources, complicate scheduling, adversely impact clinic revenue streams, and introduce significant uncertainty into daily clinical operations. Many factors have been cited as indicators of patient no-show including patient demographics, medical conditions, physician characteristics, patient–physician interaction, clinic access and administrative processes, and environmental factors [2, 3, 7–9, 11]. Bean and Talaga [2] collected 4 months of appointment data and considered the effects of physician's specialty, appointment lead time, patient age, and patient gender on patient no-show rates. They identified patient subgroups with significantly different no-show rates. The average no-show rate of each subgroup was then used to predict no-show behavior. Dervin et al. [7] constructed a regressive prediction model on ten variables using data from 100 appointments over a 1 month period. Goldman et al. [11] sampled 1,181 appointments over a 2 month period and created a no-show model using multivariate logistic regression analysis with four factors; patient age, race, attendance history, and psychological problems. Unfortunately, these and other studies do not present consistent conclusions. This indicates that important no-show predictors vary across clinics and predictive models have to be configured based on the individual clinic's background and circumstance. Further, it is of note that these no-show studies were performed on historical data recorded under traditional long term appointment scheduling conditions. As open access is implemented, most practitioners expect significant no-show reductions, which implies that no-show prediction models can be quickly outdated. Thus, one of the first steps in the configuring open access for a given clinic is to develop a process for assessing and updating no-show prediction models.

Looking briefly at the literature on appointment scheduling, Cayirli and Veral [4] provided an extensive review of the appointment scheduling literature. They categorize the appointment scheduling literature by the following attributes: (a) static vs. dynamic; (b) performance measures; (c) appointment system design; and (d) methodology. The following, briefly discusses (a)–(d) and cite representative papers. For a detailed discussion, we refer the reader to [4].

In static appointment scheduling, all decisions about appointment times are made prior to the start of a session, whereas in the dynamic case, appointment times are adjusted as patients arrive for service. Most outpatient literature deals with the static case, which typically involves N punctual patients with independent and identically distributed service times, to be scheduled for a single session with a single physician. Complications include physician lateness, non-punctual patients, and multi-stage check-in, service, and check-out procedures. A representative set of recent static papers includes [14, 25, 29].

Performance measures dictate how a given schedule is to be evaluated. These are categorized as time, congestion, or fairness based. Time based measures weight some function of patient waiting, physician idleness, and staff overtime. Congestion measures capture features such as queue length and waiting room overcrowding, and fairness measures try to distribute patient waiting time evenly over the day [20].

Appointment system design is specified by three parameters, the "block," the number of patients arriving at the beginning of an appointment period, the "initial block," the number of patients arriving for the initial appointment, and the "interval," the length of the appointment interval which is either fixed or variable. For example, the Individual-block/Fixed-interval is a typical design in which one patient is scheduled to arrive at the beginning of each appointment interval and each interval is of equal length. Also, appointment systems can be designed to use patient classification systems, which try to provide better estimations of service times and no-show probabilities. For representative system design studies in complex environments, the reader is referred to [5, 13, 16, 17].

There are two classes of methodology: analytical studies and simulation. Analytical papers use queuing theory, mathematical programming, and dynamic programming and tend to focus on the basic appointment scheduling problem with limited consideration of patient-based environmental factors such as no-shows and walk-ins. The simulation studies focus on comparing detailed appointment scheduling systems in complex environments. Representative analytical and simulation papers include [18, 25, 29] and [1, 5, 13], respectively. Further, [15] provides a review of simulation studies in health care clinics up to 1999.

Finally, although there is some literature providing high level discussion of open access, such as [22], there is little quantitative modeling of open access clinics. Giachetti et al. [10] provides an exception. They develop a system dynamics model of an open access clinic focused on reducing patient cycle time. Unfortunately, they do not address improvements in patient access and quality of care as performance measures, thought to be vital. This dearth of quantitative modeling and optimization research focusing on open access is a huge impediment to successful implementation, and the intent of this research to help fill this gap.

3 Methodology and modeling

This section describes the methodology followed in performing this work (please see Fig. 3). The first step was to design the project. In collaboration with clinical partners, the effects of several open access variables on continuity of care and patient flow in the clinic were studied. To accomplish this, a decision was made to develop a simulation model that would encompass the patient call-in process, patient no-show probabilities based on significant clinic and patient attributes, and the patient arrival process and flow within the clinic. After making these decisions, list of input data needing to be collected, analyzed, and developed for the study was generated, and methods of data analysis both from published methods and prior experience were selected. A simulation framework that would both integrate and separate the patient call-in process and patient flow within the clinic was also

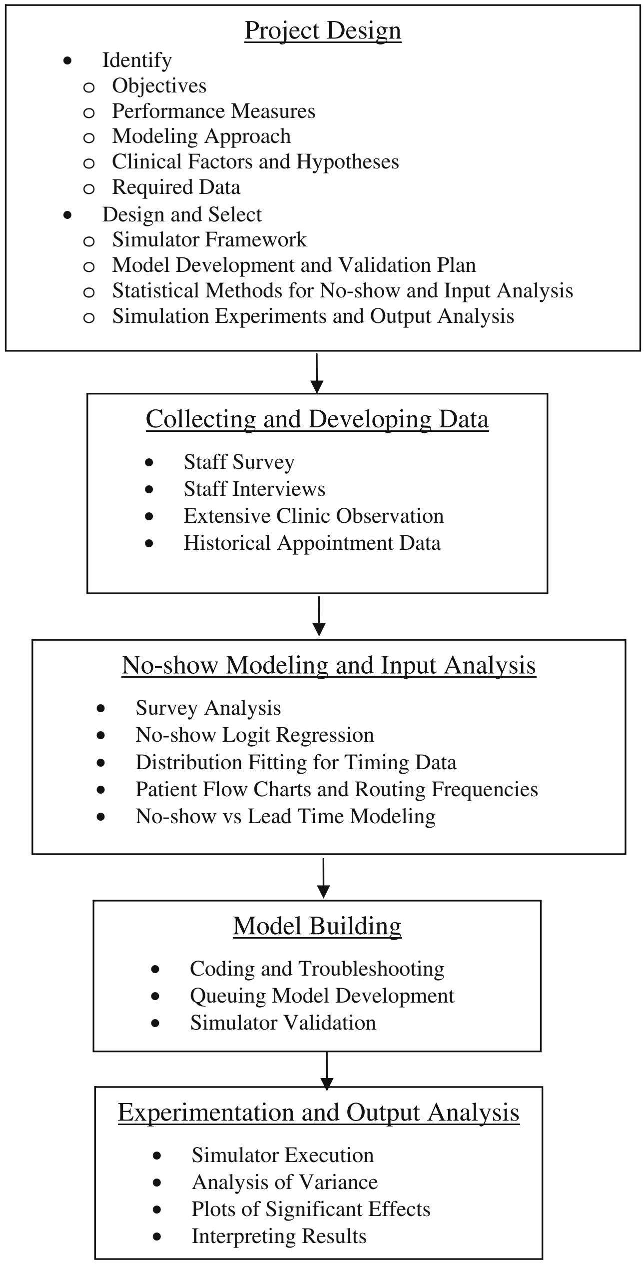

Fig. 3 Project methodology

developed. The next step was planning the model development and validation stages, and developing initial hypotheses and designing experiments for testing these. After collecting and analyzing input data, constructing and testing the no-show model, and building and validating simulation models, experiments were preformed and hypotheses tested. The following subsections discuss several aspects of these steps in more detail.

3.1 Performance measures

The performance measures considered in this work were patient continuity of care and clinic throughput in the clinic. Few studies have addressed the continuity of care issue, which is critically important since patients who see their own physicians, the physicians who know them best, tend to receive better treatment at lower cost. For example, a physician unfamiliar with a patient's characteristics might prescribe medication or order tests that the patient's regular physician would not. Thus, continuity of care is important for patient health and for controlling costs [12, 27, 28].

Clinic throughput is a measurement of the overall effect of the daily demand, the actual no-show rate of the clinic and the number of appointments successfully booked with a patient's care group. Clinic throughput as a system was selected as a performance measure since open access is intended to help stabilize the clinic operating environment by reducing patient no-show.

Continuity of care was measured by using the fraction of patients able to obtain appointments with their desired physician (or a member of their care group), and clinic throughput by the number of patients checking in.

Other relevant statistics collected from the simulation were as follows:

1. Number of appointments booked;
2. Number of appointments booked with provider/provider group;
3. Number of patients double booked;
4. Patient cycle time in the clinic.

3.2 Open access variables

The variables felt to be most important according to the clinical collaborators include:

1. Fraction of patients using open access;
2. Scheduling horizon or appointment lead time, i.e., how far in advance non-open access patients can schedule appointments;
3. Provider care groups, small groups of physicians who care for one another's patients;
4. Overbooking procedures.

The fraction of patients on open access indicates the patient population being served on open access scheduling. For example, if 25% of the clinic's patients require recurring, periodic appointments, then the clinic might want to use long term scheduling for this 25% and place the other 75% on open access. This, along with no-show rates, will influence the proportion of daily slots that the clinic needs to dedicate for open and long term scheduling purposes. It will also require that the clinic select a scheduling horizon within which to book these longer term appointments. The length of this horizon represents the maximum possible appointment lead time, which is commonly believed to affect patient no-show.

As previously mentioned, physician work patterns have to be closely considered when using open access. For example, if a patient's physician consults only on Mondays and Tuesdays and the patient calls on Wednesday, the scheduler might either try to schedule the patient for another physician or ask the patient to call back on Friday, neither of which seems satisfactory. One solution is for the physician to participate with other physicians in a provider care group. Within such a group, physicians become familiar with and help treat one another's patients, and, ideally, a large part of the clinic week could be covered by the combined schedules of physicians in the group. Provider care groups seem especially important in teaching environments where a large number of the consultations are done by residents who are under the supervision of the teaching physicians. Thus the effect of provider care groups composed of teaching physicians and residents was a major concern for the clinical partners.

Overbooking is useful in situations where there is a significant chance of no-show. Overbooking has been used in airline scheduling for many years (see [26] for an engaging review of the evolution of airline overbooking into an acceptable practice). Clinical overbooking, which is necessary to prevent under-utilization of clinic resources and physician idle time, differs significantly from airline overbooking and thus the airline models are not applicable (for a detailed discussion, see [23]). In this paper, a simple double-booking policy that allows at most two patients to be booked to a slot is applied, and then only if the likelihood of both showing up falls beneath a specified threshold-0.6 in this work, are patients double booked.

3.3 No-show and input modeling

As discussed in Section 3.1, after deciding on the modeling objectives and approach, the types of input data thought necessary were listed. This list included (1) the patient and clinical attributes that physicians and staff felt were most important in predicting patient no-show; (2) historical no-show data categorized with respect to these important attributes; (3) patient call-in rates with proportions of patients exhibiting important no-show attributes; (4) detailed clinic operations, capacities, and flow of patients within the clinic; and (5) timing data associated with each of the important clinical functions. This data and information were collected and developed over a period of several months, during which surveys, interviews, and extensive on-site observations were conducted.

Thirty-eight clinic staff members were also surveyed on what they felt were the most important factors impacting no-show behavior at their clinic. They identified age, insurance type, attendance history, appointment session (morning or afternoon), appointment type (new or returning), weather, waiting time of previous visit, and appointment lead time (how far in advance an appointment is booked). Two years worth of appointment and no-show data were then collected for the first six variables, as there was no data available for the 'waiting time of previous visit' and 'appointment lead time.' The data was collected from the clinic's historical records, categorized with respect to these six indicators, and a logistic response function was constructed to estimate the probability of a patient no showing. The session, weather, insurance, and age group, along with several two-factor interactions were found to be statistically significant for this clinic. Figure 4 demonstrates the relationship between the observed and predicted no-show rates for 960 patients with more than 30 appointments. The observed and predicted rates agree overall, with an R^2 value of 0.8071 indicating a reasonable model. The weighted standard prediction error based on the frequency of appointment category is 3.6% (for more details, see [24]).

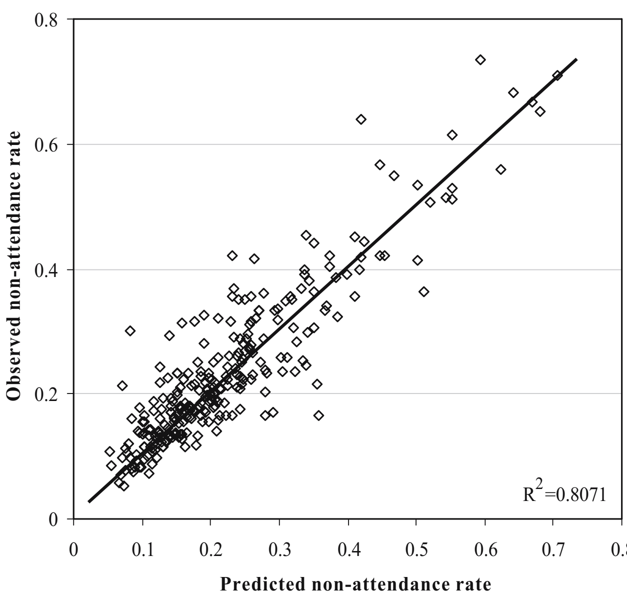

Fig. 4 Observed and predicted no-show

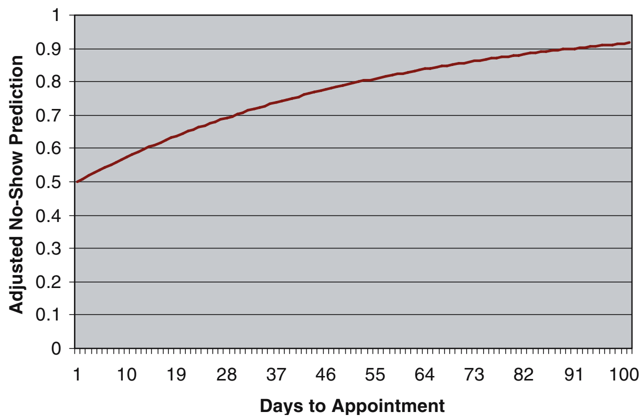

Fig. 5 Proposed no-show vs lead time model

The historical no-show data collected was recorded during a period when lead times could be as great as 6 months. Unfortunately, the impact of appointment lead time on patient no-show could not be considered since this data was not recorded. The clinical partners believed that lead time would have a significant effect, and so to capture this, the no-show rates were adjusted according to the function $f(x) = 1 - 0.5{*}e^{-0.017x}$, where x is the appointment lead time. The exponential form was selected from a number of possible forms including a linear decreasing function and adjusting the no-show rate according to a constant factor. The memoryless property of the exponential was determined to be most suitable because (1) each day is independent as is the patient's need for an appointment and (2) the exponential function is able to capture the diminishing effects of the marginal changes in the no-show probability. In an effort of conservatism, the function was modeled so that the no-show rate would improve at most by half, and the decay constant of 0.017 was found to best fit the description of this distribution. As illustrated in Fig. 5, this model will reduce a patient's estimated no-show rate by 50% if the patient is scheduled within one day (a lead time of zero). For example, if a patient's estimated no-show probability is 30% and the patient is scheduled for an appointment on the day following the appointment call, the model will estimate the patient's no-show probability to be 15%.

For clinic operations and patient flow, extensive staff interviews and observations recording the arrival and flow processes of approximately 2,450 patients over a 4 week period were conducted. Patient arrival times, check-in times, waiting-room times, time in consultation with nurses and doctors, and check-out times were also collected. The clinic operates from 8:00 to 16:30 or until the last patient is discharged. Appointments are scheduled for 15 min for returning patients and 30 min for new patients. These times are increased slightly for residents. Patients check-in with

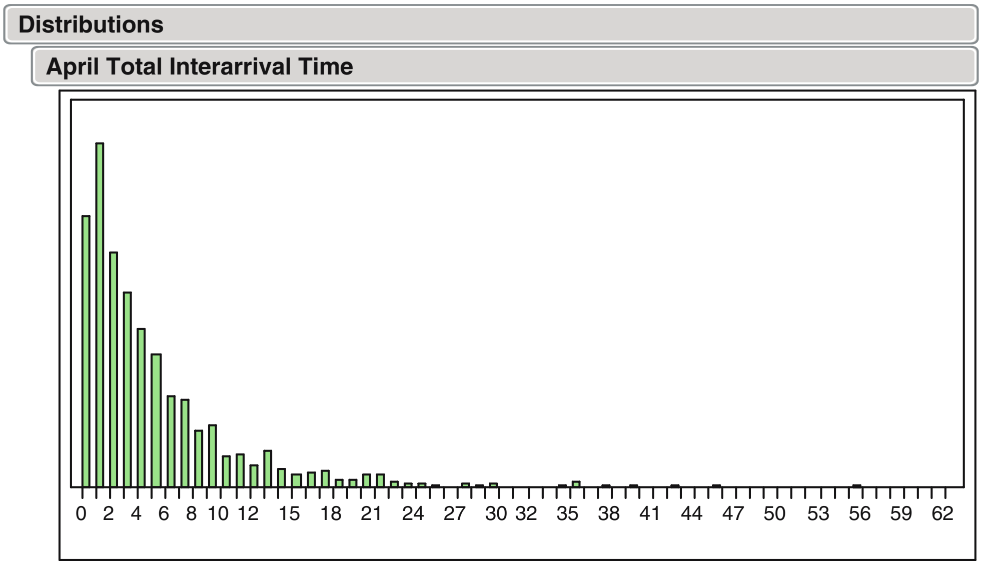

Fig. 6 Observed patient interarrival times

one of two Patient Service Assistants (PSA) at the check-in desk and then wait until being called to the examination room. After being called, the patient is either be assessed by a physician (40% of patients), a nurse (27% of patients), or both (33% of patients). After consultation, the patient goes to check-out, a station staffed by two other PSA's who book follow-up appointments if necessary. In this clinic, faculty physicians work two days per week and residents work one. The clinic has seven nurses, ten physicians, and 20 residents, and, on any given day, two physicians and three residents are scheduled.

Even though each patient is scheduled for an individual slot, overall patient arrival times followed an exponential distribution, as illustrated in Fig. 6. Furthermore, it was found all service times to be exponential as well. These two distributions were fit using the JMP statistical software. The rates are summarized in Table 1. Figure 7 illustrates patient flow within the clinic.

3.4 The simulation model

The simulation framework consists of two models that can be run independently or in an integrated fashion. The first models the patient call-in and scheduling process and the second models the patient arrival and flow process through the clinic.

Table 1 Simulation model parameters

	PSA Check-in	Physician Consult	Nurse Consult	PSA Check-out
Mean Service Rate (patients/min)	0.2	0.15	0.03	0.53

This scheduling logic is illustrated in Fig. 8. Patient call-ins are modeled as a Poisson arrival process with a rate computed from clinic data. Each call-in is randomly assigned a set of attribute values corresponding to the significant no-show predictors discussed in Section 3.3, a primary care physician (or provider care group), and a designation as open access or long term. The simulation attempts to schedule those patients which were designated as open access patients within an open scheduling horizon by randomly assigning them to an unbooked slot on that particular day. Long term patients can be scheduled anywhere across a long term scheduling horizon, in this work, either 30 or 60 days. Patients who cannot be scheduled with their primary physician may be scheduled with other physicians in the provider care group or double-booked. If neither of these is possible, the patient is scheduled with other physician who has an opening.

Figure 7 presents the logic of the clinic flow model which follows the procedures and parameters described above and follows the parameters based on actual flow observations. This model accepts as input patient arrivals according to the schedule generated by the scheduling model. Some arriving patients are terminated as no-shows before they enter the check-in queue. Although several patient routings through the clinic are possible, each will involve some combination of check-in, consulting with a nurse and/or physician, scheduling follow-up appointments (for patients on longer term scheduling), and checking out.

3.5 Model validation

To verify the simulation model, its performance was compared to a queuing network model of the clinic

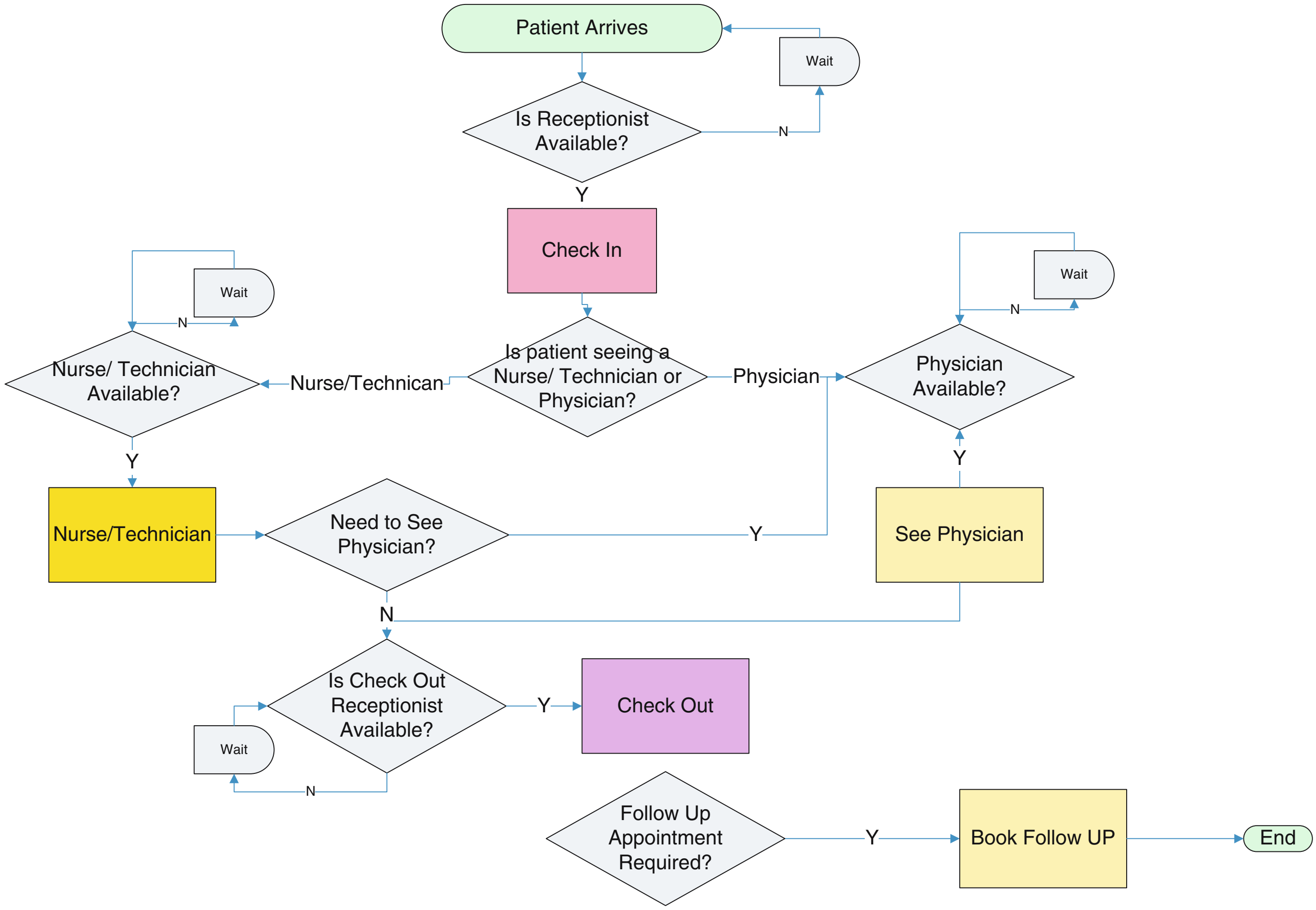

Fig. 7 Clinical patient flow

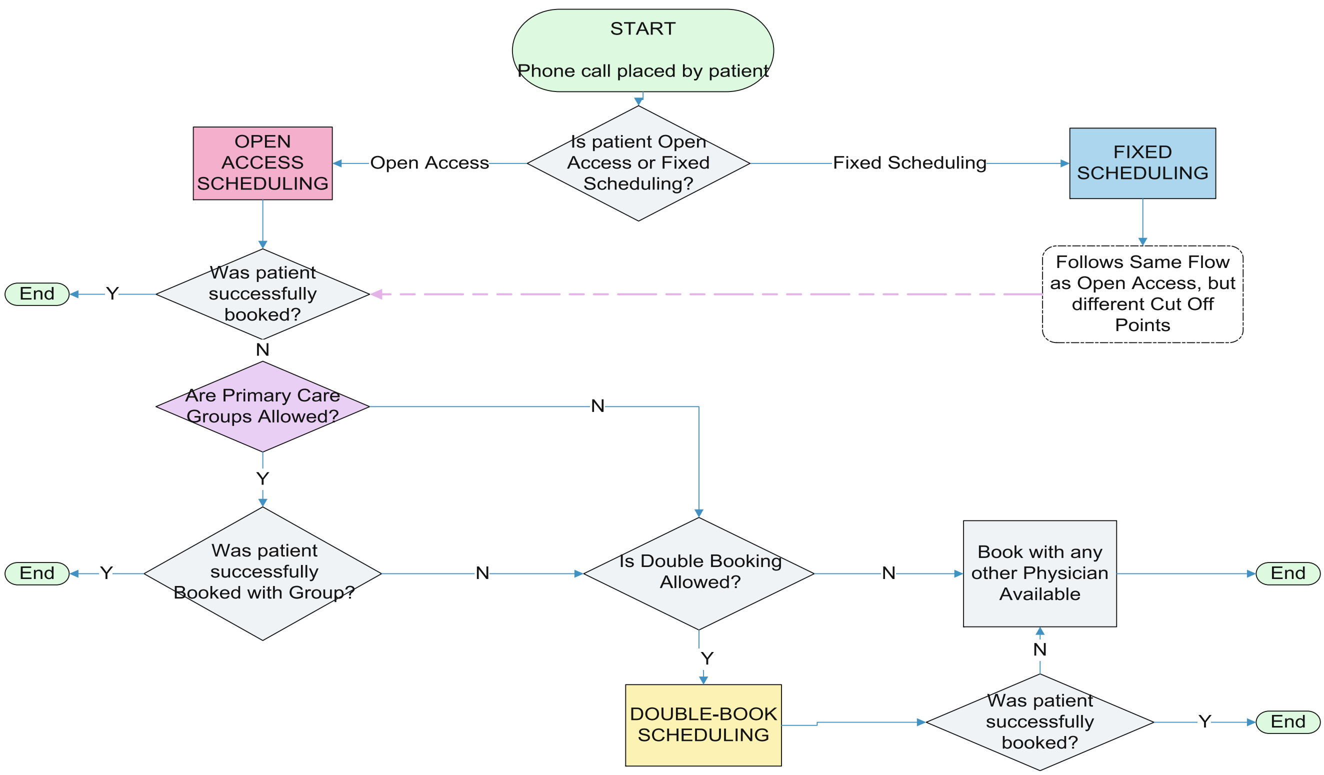

Fig. 8 Appointment scheduling logic

Table 2 Validation results

	Simulation Model	Observed Data	Queuing Model
Average Time in System (min)	43.6	45.8	38.2
Average Number of Patients in MD Station	0.65	n/a	1.05

operations. The queuing model itself was validated early in the project against observed data and was found to perform well with validation results listed in Table 2. The queueing model was a simple, less intricate model than the simulation model, and thus easier to validate. Once it was validated, it was used to verify the performance of the simulation model. Service times and rates in both the queuing and simulation model were set according to the timing data collected. There was a reasonable agreement between the two models on measures such as patient time in system and average queue lengths and strong agreement between the time in system in the simulation model and observed data. It is of note that there are fundamental theoretical differences between the simulation and queuing models. Unlike the simulation model with distinct queues for each resource at a service station, the queuing network has aggregated resources at each station with a single queue for each server. Thus, as expected, the number of patients is larger in a single queue system when compared to the multi-queue simulation model. Furthermore, the steady state analysis of the queuing network represents a continually running clinic, whereas the simulated clinic operates for only 9 h a day. Therefore the differences in these measures are expected and also serve as good indicators of deviation from steady state.

Considerable time was spent running simulation pretrials and assessing the behavior and believability of the simulation model and its outputs. After a month of this type of work, it was felt that the models were providing a valid representation of the actual clinic.

Table 3 Null hypotheses for 2^4 full factorial design

Hypotheses Tested by a 2^4 Full Factorial Design
1. Continuity of care is not affected by fraction of patients on open access.
2. Continuity of care is not affected by appointment lead time for long term patients (scheduling horizon).
3. Continuity of care is not affected by provider care groups.
4. Continuity of care is not affected by double-booking.
5. Clinic throughput is not affected by fraction of patients on open access.
6. Clinic throughput is not affected by appointment lead time for long term patients (scheduling horizon).
7. Clinic throughput is not affected by provider care groups.
8. Clinic throughput is not affected by double-booking.

3.6 Model execution

The two-phased discrete-event simulation model was constructed using Automod 11.2. Each experimental scheduling policy was run for a 90 days with three iterations. To reflect the true booking state of a clinic, the length of the warm-up period was the same as the appointment lead time for non-open access patients. For example, if the long term scheduling horizon was 30 days, the warm up period was set to at least 30 days. The following section will discuss the experimental design and results.

4 Hypothesis statements and design of experiments

The main hypotheses (stated in Table 3) are the straightforward default hypotheses tested by a 2^4 full factorial design. Three replications were performed and a second-order model is assumed. The three- and four-factor interactions were used to estimate experimental error. Table 4 provides the levels of the experimental factors that were discussed in the preceding section. These levels were developed in discussions with clinic staff and were deemed to be reasonable settings for the clinic. To enable a systematic exploration of the design specifications, the levels were set as far apart as possible clinic resources allow.

5 Results

This section details the results of the model. The ANOVA tables for an α=0.05 and effect plots for the two performance measures: continuity of care and clinic throughput are presented. The significant effects are interpreted and discussed as well. Table 5 provides the detailed results of the 2^4 design. The negative sign indicates that a factor is set at its lowest level, while a positive sign is a factor set to its highest level. For example Test 2 would be in the case in which the fraction of patients allowed on open access is set at 75% of the patient base, while the appointment lead time for those patients not on open access

Table 4 Experimental factors

	Factors	Low Level (−)	High Level (+)
A	Fraction of patients using open access	25	75
B	Appointment lead time (scheduling horizon)	30	60
C	Number of doctors in a “provider care group”	1	3
D	Allow double booking	No	Yes

Table 5 The 2^4 design

Test	Fraction of Patients Using Open Access X_1	Lead Time X_2	Number of Doctors in a "Provider Care Group" X_3	Allow Double Booking X_4	Mean Value for Continuity of Care (Probability of Obtaining Appointment)	Confidence Interval for Continuity of Care	Mean Value for Throughput	Confidence Interval for Throughput
1	−	−	−	−	0.879	(0.876,0.881)	6,168	(6,034,6,303)
2	+	−	−	−	0.679	(0.676,0.682)	6,787	(6,643,6,931)
3	−	+	−	−	0.880	(0.878,0.882)	4,939	(4,836,5,043)
4	+	+	−	−	0.668	(0.659,0.676)	6,154	(5,962,6,345)
5	−	−	+	−	0.940	(0.936,0.944)	6,246	(6,148,6,344)
6	+	−	+	−	0.819	(0.810,0.827)	6,668	(6,545,6,791)
7	−	+	+	−	0.938	(0.935,0.940)	4,959	(4,884,5,034)
8	+	+	+	−	0.818	(0.816,0.819)	5,676	(4,596,6,756)
9	−	−	−	+	0.910	(0.909,0.912)	6,318	(6,288,6,348)
10	+	−	−	+	0.727	(0.720,0.734)	6,877	(6,790,6,965)
11	−	+	−	+	0.905	(0.902,0.909)	5,026	(4,981,5,072)
12	+	+	−	+	0.723	(0.719,0.728)	6,240	(6,152,6,321)
13	−	−	+	+	0.944	(0.937,0.950)	6,175	(6,033,6,317)
14	+	−	+	+	0.839	(0.828,0.849)	5,999	(5,977,6,022)
15	−	+	+	+	0.948	(0.946,0.950)	4,903	(4,888,4,918)
16	+	+	+	+	0.844	(0.840,0.848)	6,178	(6,081,6,277)

is 30 days, the number of doctors in a care group is 1 and double booking in not allowed. As all the confidence intervals are short, three replications of each test was deemed sufficient.

5.1 Continuity of care

From the ANOVA of Table 6 and the corresponding main effects plot (Fig. 9), all main effects are significant except appointment lead time (scheduling horizon). Also, all two factor interactions that do not contain appointment lead time are also significant (Fig. 10 plots the most significant factors: fraction of patients using open access and the size of provider care group). The simulation data supports rejecting null hypotheses 1, 3, and 4, but not null hypothesis 2. Further, the interaction between provider care group and fraction of patients on open access indicates that provider care groups become essential for maintaining continuity of care as the fraction of patients on open access increase. The conclusion here is that *for a clinic to successfully serve a large percentage of the patient population on open access, it is necessary to develop provider care groups and double booking policies*.

5.2 Clinic throughput

The ANOVA of Table 7 shows that only fraction of patients on open access and appointment lead time significantly affect clinic throughput (Fig. 11), i.e., the ANOVA supports rejecting null hypotheses 5 and 6 but not null hypotheses 7

Table 6 ANOVA for continuity of care

Source	DF	SS	MS	F	P
Allow Double Booking	1	0.003078	0.0031	264.93	0
Provider Care Group	1	0.03219	0.0322	2,770.36	0
Fraction of Patients	1	0.094198	0.0942	8,106.83	0
Lead Time	1	0.000009	0.0000	0.73	0.431
Allow Double Booking[a]Provider Care Group	1	0.000631	0.0006	54.33	0.001
Allow Double Booking[a] Fraction of Patients	1	0.000391	0.0004	33.65	0.002
Allow Double Booking[a]Lead Time	1	0.000012	0.0000	1.03	0.357
Provider Care Group[a] Fraction of Patients	1	0.006723	0.0067	578.56	0
Provider Care Group[a]Lead Time	1	0.00004	0.0000	3.46	0.122
Fraction of Patients[a]Lead Time	1	0.000005	0.0000	0.45	0.531
Error	5	0.000058	0.0000		
Total	15	0.137336			
R^2=99.96%					

Letter a indicates two-factor effects.

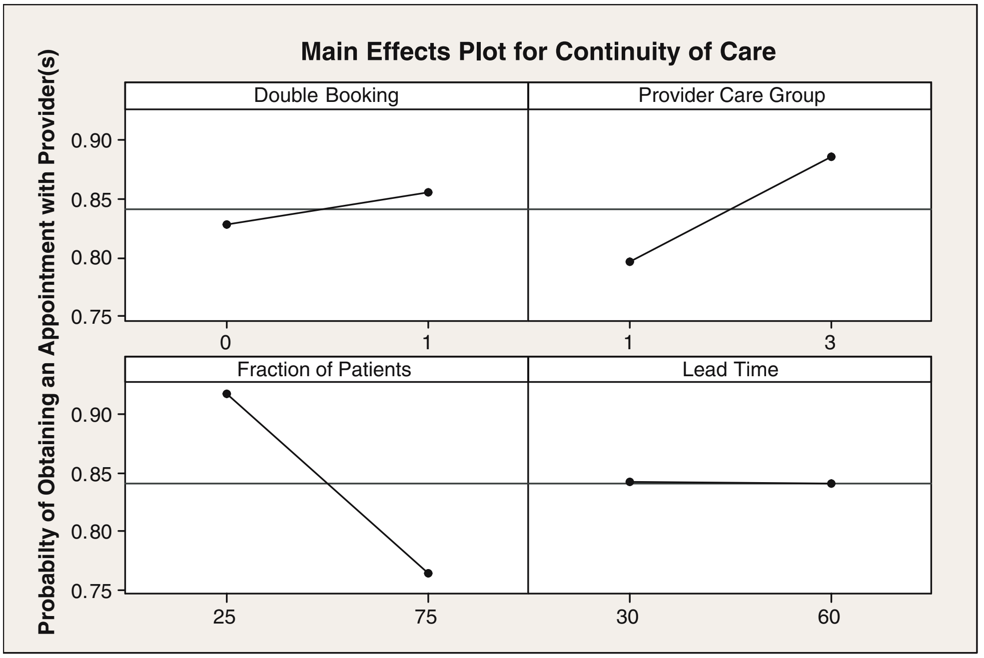

Fig. 9 Main effects plot for continuity of care

and 8. Though it may appear to be surprising that the ANOVA results indicate that double-booking does not significantly affect clinic throughput, this result is likely specific to the clinic and arrival rates. Closer examination of the simulation results revealed that on average, a relatively low volume of appointments were acquired through double booking means (2.2% of the total volume). It is also of note that of all the double booking attempts, 84% of patients attempting to double book were able to successfully meet the double booking criteria. Thus, as double booked appointments did not present a substantial volume of appointments, its impact on clinic throughput was not significant. The two factor interaction between fraction of patients and appointment lead time is also significant (Fig. 12). From Fig. 12 one can note that as lead time (horizon) increases, clinic throughput drops, especially when large percentages of the patient population are on long term scheduling.

As the fraction of patients on open access increases, the effect of lead time is diminished due to the more limited number of people being scheduled long term. Recall the function used to model the effect of lead time on no-show. When patients were able to schedule an appointment for the

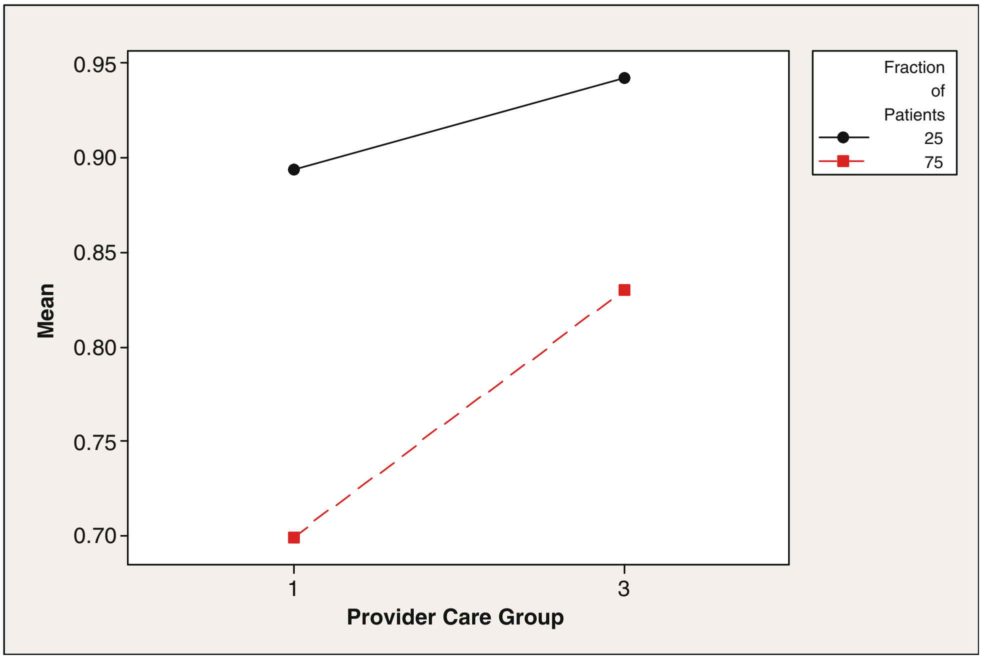

Fig. 10 Two way interaction between fraction of patients and provider care group

Table 7 ANOVA for clinic throughput

Source	DF	SS	MS	F	P
Allow Double Booking	1	895	895	0.02	0.905
Provider Care Group	1	181,547	181,547	3.23	0.132
Fraction of Patients	1	2,135,739	2,135,739	37.95	0.002
Lead Time	1	3,207,980	3,207,980	57	0.001
Allow Double Booking [a]Provider Care Group	1	31,241	31,241	0.56	0.49
Allow Double Booking [a]Fraction of Patients	1	621	621	0.01	0.92
Allow Double Booking [a]Lead Time	1	78,353	78,353	1.39	0.291
Provider Care Group[a] Fraction of Patients	1	116,452	116,452	2.07	0.21
Provider Care Group[a]Lead Time	1	11,008	11,008	0.2	0.677
Fraction of Patients[a] Lead Time	1	561,625	561,625	9.98	0.025
Error	5	281,412	56,282		
Total	15	6,606,871			
R^2=95.74%					

Letter a indicates two-factor effects.

next day, their no-show rate was decreased by 50% to account for the reduced lead time. Thus, the results clearly illustrate the positive effect of reducing no show rate, although the claim is tentative as the lead time/no-show model is not based on observed data. However, it can be confidently concluded that *open access can provide significant increases in clinic throughput when coupled with intervention strategies to reduce no-shows*.

The results are summarized in Table 8. Based on this table, it is also interesting to note the following:

1. Fraction of patients on open access affects both performance measures. As the fraction increases, continuity of care goes down and clinic throughput increases.
2. Appointment lead time does not affect continuity of care but does affect clinic throughput. As the lead time increases, throughput goes down.
3. Provider care groups have a positive effect on continuity of care but no effect on clinic throughput.
4. Double-booking has a positive effect on continuity of care but no effect on clinic throughput.

Note that (1), (3), and Fig. 10 indicate that the negative effect that fraction of patients on open access has on continuity of care can be partially, but not completely, offset by providing provider care groups. Further, (2) indicates that no-show rates have limited impact on

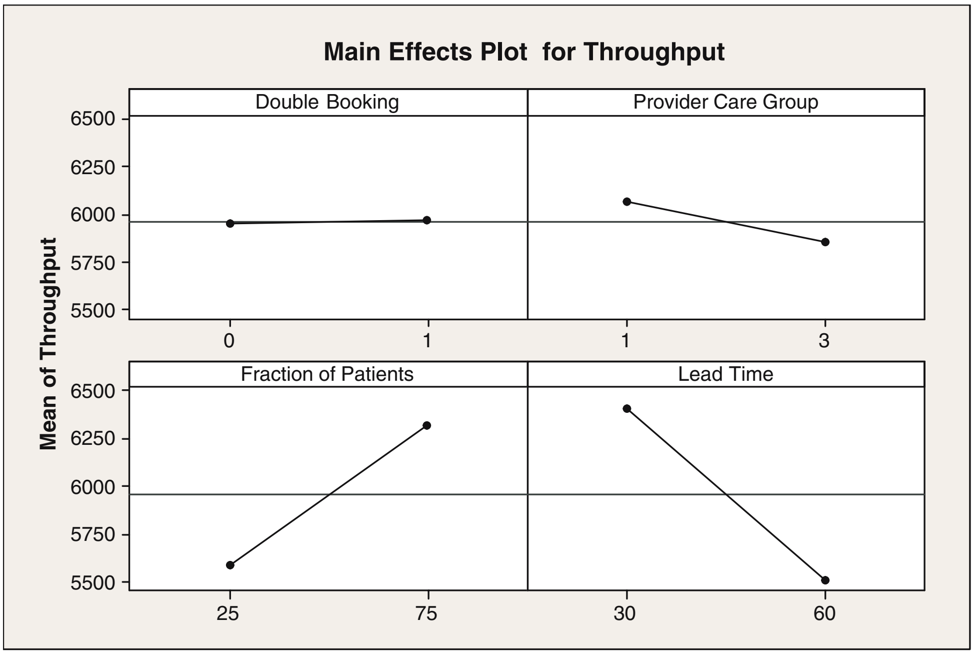

Fig. 11 Main effects plot for clinic throughput

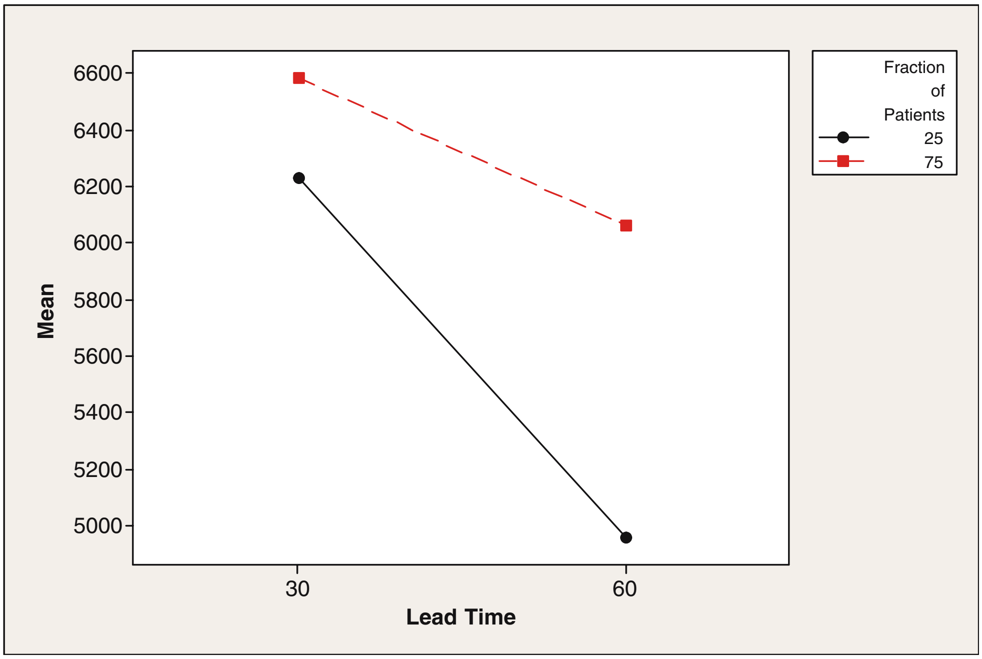

Fig. 12 Two way interaction between fraction of patients and horizon

continuity of care but significantly affect clinic performance. Finally, (4) indicates that the double-booking policy implemented in this work helps patients gain access to their physician but does not significantly increase the number of patients served by the clinic.

6 Conclusion

In this work, a simulation model was developed to study the effects of clinic parameters on open access implementation. The simulation framework proposed and implemented, integrates models of the call-in process, patient no-show, and clinic performance. The work described here is also the fundamental component of the overall modeling framework and implementation approach described in [6]. Using the methodology and an exhaustive set of data collected from a major tertiary teaching hospital with over 950 faculty physicians, the effect of various design parameters on continuity of care and clinic throughput were investigated. The analysis indicates that the fraction of patients served under open access affects both the continuity of care and the clinic throughput. Further, it indicates that double-booking has a significant effect in increasing continuity of care while appointment lead-time has a significant effect in increasing clinic throughput. Provider care groups were found to lead to significant increases in continuity of care, and that these are essential when a large percentage of patients are served on open access.

The results indicate that by moving to open access and shortening appointment lead times for long term scheduling, clinics can serve more patients. However, if a clinic is too aggressive in implementing open access, that is, if a clinic initially puts too many patients on open access, then continuity of care will be significantly compromised, resulting in higher treatment costs, and physician and patient dissatisfaction. These negative effects can be partially offset by developing provider care groups and by using some overbooking. However, these techniques

Table 8 Summary of null hypotheses rejected

	Reject	Fail to Reject
1. Continuity of care is not affected by fraction of patients on open access.	✓	
2. Continuity of care is not affected by appointment lead time for long term patients.		✓
3. Continuity of care is not affected by provider care groups.	✓	
4. Continuity of care is not affected by double-booking.	✓	
5. Clinic throughput is not affected by fraction of patients on open access.	✓	
6. Clinic throughput is not affected by appointment lead time for long term patients.	✓	
7. Clinic throughput is not affected by provider care groups.		✓
8. Clinic throughput is not affected by double-booking.		✓

require education, refinement, and assimilation by clinic staff, physicians, and the patient population, which necessitates very carefully planned, timely implementations. The types of systems analysis tools developed in this and other works are essential for achieving this smooth, timely transition from traditional scheduling to open access, and that systems analysis maximizes the probability of success.

The sources of error related to these results include possible inaccuracies associated with the patient specific no-show adjustment function. Historical data linking appointment lead time and no-show is required as is a more throughout function approximation. However the function as presented was deemed sufficiently robust to be used as a benchmark for similar studies. There are many possible extensions to the basic set of tools presented in this work. A more generic model can be constructed to allow for easier inter-clinic transferability. This work could be extended to consider a range of operating levels for the four factors studies rather than their extremes and the optimal operating conditions could be established using response surface optimization. Experimentation with the arrival rate increases and its impact on overbooking volumes would be insightful.

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