Health Care Manag Sci (2011) 14:135–145
DOI 10.1007/s10729-010-9145-4

Using simulation modeling to improve patient flow at an outpatient orthopedic clinic

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Received: 21 June 2010 / Accepted: 24 November 2010 / Published online: 9 December 2010

Abstract We report on the use of discrete event simulation modeling to support process improvements at an orthopedic outpatient clinic. The clinic was effective in treating patients, but waiting time and congestion in the clinic created patient dissatisfaction and staff morale issues. The modeling helped to identify improvement alternatives including optimized staffing levels, better patient scheduling, and an emphasis on staff arriving promptly. Quantitative results from the modeling provided motivation to implement the improvements. Statistical analysis of data taken before and after the implementation indicate that waiting time measures were significantly improved and overall patient time in the clinic was reduced.

Keywords Outpatient clinic · Discrete event simulation · Process improvement · Patient waiting

1 Introduction

Visiting hospital outpatient clinics is a very common way for patients to access health care. These clinics typically schedule appointments for patients in advance, and patients arrive to the clinic expecting service to begin at their scheduled time. However, due to the patient arrival time and service time variation described in Noon, Hankins, & Cote [1], patients end up waiting even though they have reserved time slots. Further, it is common practice at many outpatient clinics for providers to book multiple patients at the same time. Part of the reason for this is to ensure that patients are always available to see doctors or other expensive, scarce health care resources. However, if all scheduled patients show up on time or early, significant patient waiting is a certainty.

The concern with this waiting is the patient dissatisfaction it may cause. In their study of outpatients, McCarthy, McGee, & O'Boyle [2] found that 64% of patients rated waiting times as unsatisfactory. In addition, that study reported that a significant number of patients who decline to attend their appointment do so because of the expectation of long waiting times. Such "no-shows" are an obviously undesirable occurrence where they can be avoided. In the similar environment of appointments for physicians, survey results show patient waiting time as one of the top three differentiators for "best practice" offices versus average offices [3]. This suggests that for health care systems where patients have a choice of health care providers, shorter waiting times are apparently a competitive advantage.

How much waiting at an outpatient clinic is acceptable depends on many factors. Individual "patience", the type of clinic, and the pleasantness of the waiting area all affect patients' tolerance for waiting. As Cartwright & Windsor [4] note, patients will accept short waiting periods. However, there is a limit to the length that patients will accept graciously. The study by Huang [5] found that patients who arrived on time for appointments were

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satisfied with wait times of 37 minutes or less. In 1991 the UK's National Health Service's Patient's Charter set a 30 minute target for appointment waiting times [6]. Thus, it seems that wait times in the neighborhood of a half hour are considered acceptable.

In this research, we study the patient flow at an outpatient orthopedic clinic in Calgary, Alberta. The clinic is nicknamed the "cast clinic" since many patients come to have casts put on and taken off—we will use this term in the remainder of the article. At the start of the study, waiting times and patient congestion at the clinic were substantial. The average time patients spent at the clinic was nearly an hour and a half, with the majority of that time spent waiting. It was not uncommon for patients to wait over two hours after their assigned appointment times.

The negative effects of waiting on patients are well documented (e.g., [7]). However, clinic staff also experience negative effects due to patient congestion. Growing lines of patients put the staff under significant work pressure and often requires them to deal with unhappy patients. In the long run, such pressure can create morale problems and likely contributes to absenteeism. Therefore, the researchers for this study were brought in to help the cast clinic diagnose the causes of poor patient flow and to identify effective solutions. We used simulation modeling as the main tool to help in our diagnostic and improvement efforts.

One major contribution of our work is to show how a structured analysis of patient flow can significantly improve waiting time and patient congestion in a cast clinic. We believe our study is the first of its kind for an orthopedic clinic. Another major contribution is to show how simulation modeling and the "hard" quantitative analysis it provides can assist in convincing involved parties to implement improvements. The clinic previously attempted to improve patient waiting-time performance by testing localized initiatives using standard Plan-Do-Study-Act (PDSA) methods [8]. While this approach likely helped in creating a culture more accepting of change, the modeling we performed provided a systems perspective in addition to the quantitative evidence that showed that the improvements should work. With the preponderance of scientific staff in healthcare settings, we believe a quantitative evidence-based approach can be important for a successful implementation.

2 Computer simulation in healthcare

Many authors have suggested that computerized discrete-event simulation is a useful analysis and improvement tool in industry settings that exhibit high levels of complexity and uncertainty [9]. Because health care is one such industry, there are numerous academic studies that use it as a research method in that setting. In their review article, Jun, Jacobson, & Swisher [10], cite over 100 articles applying simulation to health care processes and systems. As simulation tools have improved and an emphasis on cost control and efficiency has become more important in health care, researchers continue to suggest its use. Ledlow & Bradshaw [11] point out the value of animation and visualization when applying simulation to health care settings, and Young [12] discusses how simulation can assist health care organizations explore alternative patient pathways with the "lean" methodology so many of them are adopting. Finally, in their evaluation of modeling methods for health care, Cooper, Brailsford, & Davies [13] note that simulation may be particularly useful where "queuing for resources, resource constraints or the interactions between individuals" are important. This would seem to encompass a great many health care settings, including outpatient clinics like the cast clinic studied in this research.

To support the use of simulation in health care, there appears to be a growing list of applied case studies in the literature. Recent examples of this are the studies of Kumar & Shim [14] and VanBerkel & Blake [15] who consider capacity planning and wait time reductions in surgical settings. Similarly, Kim, Horowitz, Young, & Buckley [16] use simulation to evaluate capacity management strategies in an intensive care unit (ICU). In more case studies using simulation, Rohleder, Bischak, & Baskin [17] discuss its use in redesigning patient laboratory sample collection sites and Brasted [18] uses it to model the case of an ultrasound waiting list. Finally, in a setting somewhat similar to that of this paper, Merkle [19] uses simulation to improve the operations at a family care clinic.

Thus, it is apparent that simulation is finding good application in health care. To this body of work, our study adds the specific setting of an outpatient cast clinic. Further, while the previous set of case studies often propose alternative modes of operation, in most cases the researchers and modeling activity were not embedded in the improvement process with the intent of implementation. In our study we take an action research approach with a focus on improving patient service. With large numbers of patients served in the cast clinic, the potential overall impact is large and changes can be implemented and their effect easily measured. Sachdeva, Williams, & Quigley [20] also show that the use of operations research tools in general, and simulation specifically, led to improved health care outcomes. We also view this approach to research in a positive light and note that our study resulted in the mutually beneficial outcomes of better patient service for the clinic studied and new knowledge for the researchers to apply and disseminate.

3 Description of the cast clinic

In this section we will describe the cast clinic's processes with a focus on its purpose, resources, and operations.

3.1 Overview

Foothills Medical Centre is the only Level I trauma centre and spine surgery hospital serving Calgary and additional suburban areas for a total patient population of around 1.2 million. The cast clinic is an outpatient clinic which accommodates the majority of outpatient orthopedic patient appointments for the hospital including fractures, some spinal injuries, hand and wrist disorders, and some joint replacement patients. The clinic sees a variety of patients including:

- New referrals
- New patients from the Emergency Department
- Repeat patients returning for review of their progress with either surgical or non-surgical treatment

The majority of patients visit the clinic multiple times during their orthopaedic care. The clinic has had an average monthly volume of 1000 appointments with some variation in recent years. The clinic is generally open from 7 am to 4 pm Monday through Friday and is closed for holidays.

3.2 Staff/resources

There have been some changes in use of the clinic by local surgeons over the past few years due to a change in practice pattern. At any given time, up to ten surgeons have staffed the clinic per week. On most days two surgeons are scheduled at the clinic. However, from one to four may be scheduled depending on holidays, vacations, and variations in surgeon and clinic schedules. Most surgeons are assisted by trainees (either resident physicians or medical students). While the surgeons drive the operations of the clinic, the following staff and resources are also key elements of the clinic's operations:

- 7 examination rooms (plus a patient waiting area);
- 2 unit clerks who check patients in when they arrive and schedule appointments;
- 2 x-ray machines, primarily used for cast clinic patients—however, some inpatients (not clinic patients) also use these machines;
- 2 x-ray technicians;
- 2 orthopedic technicians who manage cast care and dressing changes among other duties.

A variety of other staff also participate in the clinic, including residents, students, nurses, and physiotherapists. A clinic administrator oversees the management of the clinic, and a separate administrator oversees the use of diagnostic imaging equipment (x-ray) and the staff running this equipment.

3.3 Operations

Patients are assigned to see particular surgeons and the surgeons decide on the overall strategy for scheduling their patients. The unit clerks perform the actual scheduling function based on a combination of patient availability and the surgeon's preferred strategy. Daily volumes at the clinic vary significantly, but 50–100 patients are typical. A small proportion of patients "walk-in" to the clinic without a pre-scheduled appointment time. This occurrence is sometimes due to clerical errors by either staff or patients, and at other times, patients may choose to come to the clinic for emergency visits without calling ahead. If the patient has been to the clinic in the past, all reasonable efforts are made to accommodate them.

Patient flow through the clinic is highly variable. Data showed that surgeons typically had 20–30 different patient sequences through the staff and resources described above. It is not uncommon for a patient to see the same resource more than once during a visit to the clinic. Thus, patient flow is a highly jumbled and unpredictable process. Figure 1 shows a simplified version of the layout of the cast clinic used for animating the cast clinic when running simulations and Fig. 2 shows examples of two of the 18 different patient pathways for one of the surgeons.

While the patients' paths vary significantly through all the clinic resources, by a significant margin, the x-ray machines/technicians and the surgeons are the busiest resources. Essentially all patients see the surgeons and 90–95% of patients have x-rays, depending on the surgeon. Most (but not all) x-rays are pre-ordered and completed before a patient is invited in to an examination room. Other clinic resources such as the orthopedic technicians (OT) have lower patient treatment interaction utilization levels; however, they have other duties that take additional work time. These additional duties have traditionally been ill-defined but include assisting the unit clerks in administrative management and streamlining patient transfers between resources.

Overall, the clinic's structure may seem simple on the surface, but there is actually significant complexity in its operations. This makes it difficult to easily identify appropriate interventions and supports the role of modeling in identifying the causes of performance problems and options for improvement.

4 Simulation modeling process

The major steps in the modeling process were i) process understanding and data collection; ii) building a simplified

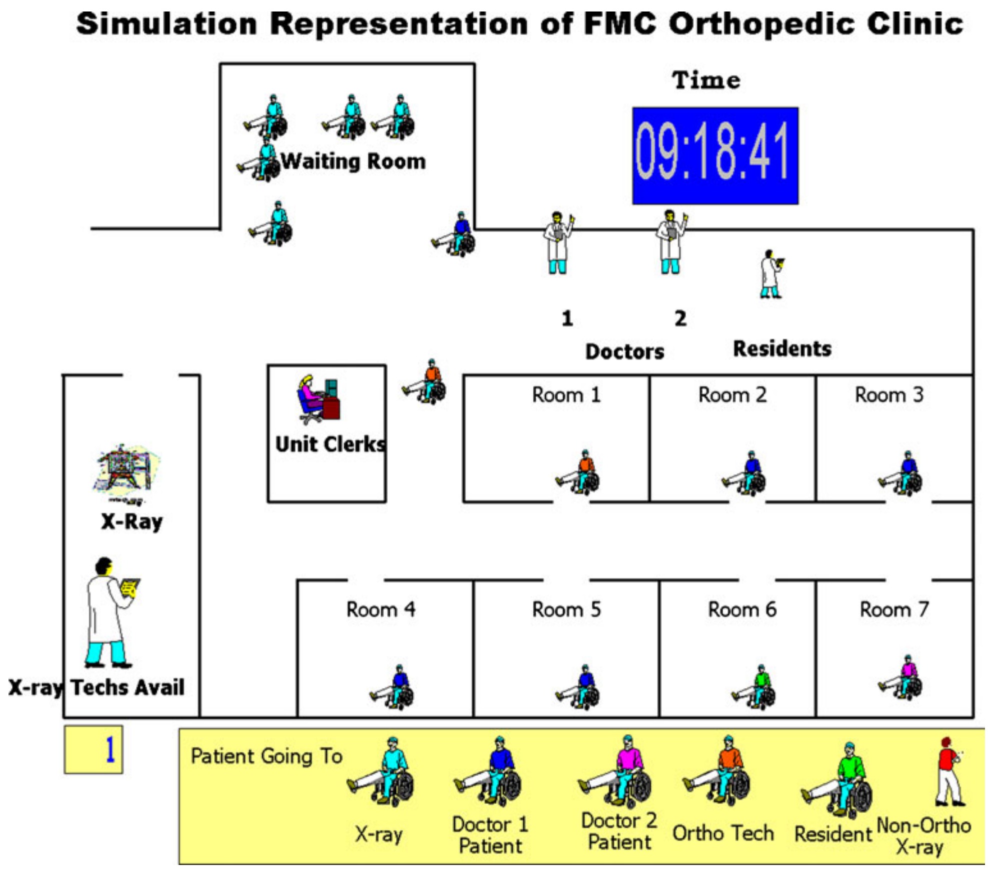

Fig. 1 Simplified physical layout of the cast clinic

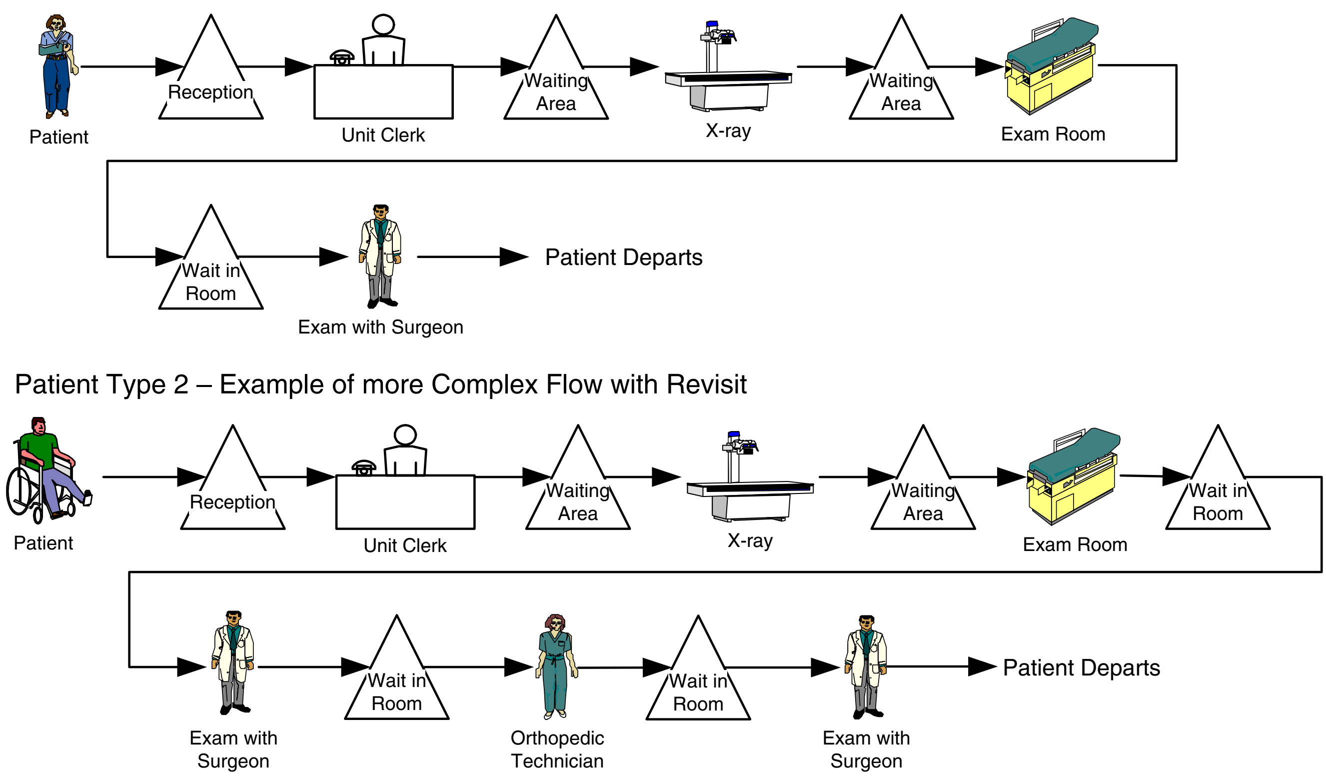

Fig. 2 Example of patient flow through resources (with waiting)

generic simulation model using the Arena Software (Rockwell Automation Technologies, Inc., version 12.0, 2007) to test scheduling options, iii) building valid models for the participating physicians to thoroughly test proposed scheduling and operational changes, iv) analyzing the model results to identify appropriate improvements to implement; v) implementing the changes suggested by the models, and vi) evaluating the system performance to determine if the implemented changes resulted in real improvement. The following will briefly discuss each of these steps.

4.1 Process description and data collection

Meetings were held with staff to understand the process flow of patients, determine a set of performance measures to be used throughout the study, and map out a data collection procedure. Five primary performance measures were chosen to quantify the impact that any changes to the clinic's processes might have: i) the total time a patient spends in the clinic, ii) the time a patient waits for an x-ray, iii) the time a patient waits for the surgeon, iv) the percentage of patients whose clinic visits were completed in 60 minutes or less, and v) the time of day when all patients had completed their visits.

The first four measures clearly relate to patient satisfaction with waiting and clinic congestion. In particular, measure iv) was included because Clinic administrators were given a target of getting all patients through the clinic in 60 minutes or less. However, it was recognized that measures i) and iv) were not completely under the control of the Clinic, as some patients were arriving very early for their appointments. As patient satisfaction is most directly related to how long a patient waits to be seen, a sixth measure, length of the initial wait in the waiting room, was added. As the patient arrival pattern is unlikely to change in the short run, a combined reduction in this measure and in measures i) and iv) would indicate that system performance has truly improved and it is not simply that patients are arriving less early to their appointments. In the long run, process improvements would hopefully lead to shorter and more consistent waiting times that in turn would lead to less variability in patient arrival times.

Measure v) was of particular interest to the surgeons due to their busy schedules that included many duties outside of the cast clinic even on days during which the cast clinic was the primary activity. Earlier completion could allow more time to attend to these other duties. Other Clinic staff may not be able to leave early due to faster completion of a day's slate of patients, but prompt completion would allow for reduced overtime or a more relaxed preparation for the next day's clinic.

Initially, data collection sheets were sent with patients for them to fill in the appropriate time stamps and resources they visited. However, while some of the data collected using this approach was useful, much of it was not precise enough for use in building a model. In particular, histograms showed that data collected by patients led to unusual spikes at 5, 10, and 15 minutes. Issues such as this "rounding" problem prompted us to use independent data collectors to obtain more precise time data. To this end, four undergraduate business students collected data in February and March 2008. Accurate data on 201 patients seen by three doctors were collected over this time period for the following categories:

1. Patient arrival times (to determine a probability distribution of the amount of time patients were early or late to their appointments).
2. Service times for all the resources (x-ray, orthopedic technician, surgeon, resident, exam room, etc.).
3. Patient paths—used to develop a frequency distribution of resource usage and sequencing (combined with previously collected patient data which was deemed accurate for this component).

4.2 Model building and validation

Collected data on patient earliness/lateness and patient service times were used as input to the ExpertFit software [21] to establish appropriate probability distributions to use in the simulation model. Through a process of evaluating statistical fit (Kolmogorov-Smirnov test) and graphical evaluation (comparing the histogram of the data to a graphical representation of the distribution function), the distributions in Table 1 were selected.

Interestingly, as in Alexopoulos, Goldsman, Fontanesi, Kopald, & Wilson [22], the amount of time that the patient was early or late for their appointment at the cast clinic was best approximated by the Johnson SU distribution (see Fig. 3). We used this distribution to offset from scheduled appointment times in the simulation models. The few walk-in patient arrivals were distributed randomly across the clinic hours. Patients were generally seen in a First-Come-First-Serve (FCFS) manner in the real system and therefore were always processed this way in the model. Because patients frequently arrived earlier or later than their appointment times, FCFS processing meant that patients could be seen in a different order than their appointment sequence. The data showed this frequently occurred in practice. The "unfair" nature of this occurrence likely contributed to the variability in patient adherence to their assigned appointment time.

After arrival, the simulated patients were routed to the appropriate resources based on the frequencies determined from the patient path data. Depending on the surgeon, some resources were explicitly modeled in all paths and some

Table 1 Example input distributions for simulation model

Purpose	Distribution (Parameters)	Discussion
Patient arrivals	Johnson SU (-4.15,14.35,0.31,.98)	Negative values = early
X-ray time	Lognormal (6.17,4.10)	
Orthopedic Tech time	Gamma (7.88,1) + 0.78	
Resident exam time	Weibull (8.38,1.69)	
Surgeon exam time Returning	SA: Weibull (9.46, 2.42) *m*=8.4* SB: LogLogistic (4.15,2.57) *m*=4.98	The distributions represent two different surgeons (A and B)
Surgeon exam time New	SA: Weibull (15.18, 2.17) *m*=14 SB: Lognormal (9.16, 9.92) *m*=9.16	These patients were not previously seen by the surgeon

* *m* mean (minutes)

were not. For example, for Surgeon A, residents always visited the patient with the surgeon and left when the surgeon left. By analyzing the data, it was clear the surgeon was the delaying resource, not the residents. Thus, the resident was not modeled explicitly for Surgeon A's patients. A resource was included if it contributed to patient delay for a particular surgeon, otherwise it was not. In this way, the model was kept as simple as possible. For the resources that were included, service times were randomly generated using the probability distributions shown in Table 1. It should be noted that while all the surgeons at the clinic are trauma surgeons their interests in treating particular types of patients differ. This helps account for some of the differences in examination times reported in Table 1.

To determine if our modeling approach was valid, we compared the model output to the performance of the actual system. Figure 4 graphically shows one evaluation for the total patient time in the clinic. This measure was the difference between when the patient left the clinic less the time the patient arrived (including total waiting and service times for all resources). As the figure shows, the confidence intervals created from the model output contain the average value from the actual system. This was true for other performance measures including x-ray waiting time and clinic end time (when the last patient left). The only measure for which there was some discrepancy was waiting time for the surgeon. For some surgeons and surgeon combinations, the model slightly underestimated this waiting time. This was likely due to the fact that the model assumed that surgeons were always available to meet with patients when not examining another patient. In practice, surgeons frequently have short interruptions that may somewhat limit their availability. This was viewed as a minor issue since the more comprehensive simulation outputs such as total patient time and clinic end time matched well with real system performance.

4.3 Identification of options for improvement

One of the key uses of the simulation model was to diagnose causes of delay in patient flow in the cast clinic. We discovered three key areas in which we could potentially produce a significant improvement in clinic efficiency without dramatically altering clinic practice.

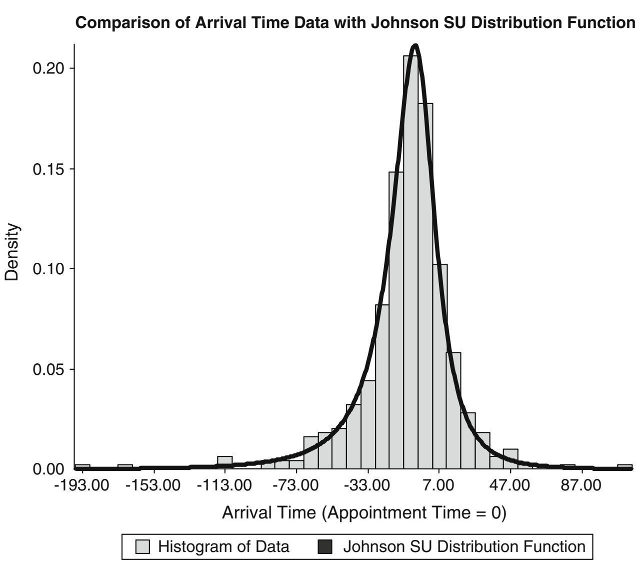

Fig. 3 Patient arrival time earliness/lateness distribution

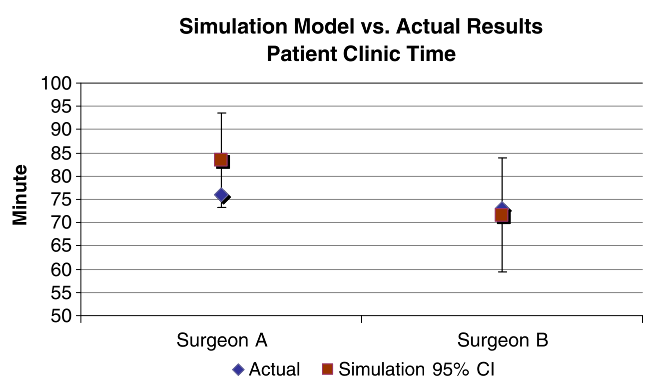

Fig. 4 Validation analysis—comparison of average clinic times

First, the model indicated that it was necessary for both of the x-ray machines to be operating continuously to avoid significant patient backlog. However, in actual practice the clinic's two x-ray technicians needed to take occasional breaks that caused one (and sometimes both) x-ray machines to become unavailable. Thus, one improvement option identified was to add a third x-ray technician to cover for breaks and to coordinate staff schedules to ensure that the two x-ray machines were always available during the busy days in the clinic.

Secondly, the model identified that the arrival of surgeons to the clinic 30 to 60 minutes after the clinic opened—a common occurrence—was another problem that, not surprisingly, caused significant delay for patients arriving early in the day's schedule. When this happened, it sometimes took until mid-morning to reduce the patient backlog. Of course, it is important that not only the surgeons but also all the rest of the staff are available when the clinic opens to ensure that patients are ready for their examinations, so the second improvement option identified was simply to ensure the punctuality of all staff members.

Thirdly, the model also identified the important role that appointment scheduling played in patient waiting time, so a revised scheduling procedure was the third improvement option. The cast clinic scheduled a block of n patients over intervals of length t. The exact value of n and t differed by surgeon and by hour of the day, but it was common practice to "front load" the schedule and have larger n values in early hours of the day (and have more patients arrive in the early hours). A typical schedule in the first hour was 5 patients scheduled for 7:00, 4 patients scheduled for 7:15, and no more patients scheduled until 8:00. Having block sizes with $n>1$ makes sense since there is significant variability in patient arrival times (see Fig. 3) and it is not desirable for the surgeons to be idle, waiting for patients. However, given that most patients arrive early, we determined that reducing the number of patients scheduled in blocks and working with consistent intervals would lead to less waiting without creating significant surgeon idle time.

Working with a "generic" model created to represent a typical surgeon at the clinic, we ran experiments to evaluate which combinations of n and t would work well. Block sizes of $n=1$ to 3 and intervals of $t=10$, 15, 20 and 30 minutes were tested. These combinations were selected as practical values that could potentially be implemented. Results showed that $n=3$ and $t=20$ was the best combination to reduce patient waiting time and simultaneously keep the time to see all patients in the clinic (and corresponding surgeon idle time) to a minimum. However, since most surgeons scheduled in 15-minute intervals, we decided to test the combination of $n=2$ and $t=15$ for possible implementation. In all cases, the number of appointments was kept the same and matched the average number of clinic appointments for each surgeon in reality.

To further improve appointment scheduling, we also considered changes in the scheduling of certain types of patients. Based on the results of Klassen & Rohleder [23], we knew that patients with greater variability in service times would be more likely to disrupt the schedule. New patients were statistically identified as having a higher mean and variance than returning patients. Therefore, for scheduling purposes we also moved these patients to the end of a surgeon's schedule.

5 Modeling results

Using simulation models of the specific surgeon and clinic configurations, we estimated the performance of the three improvement options for several key measures. Table 2 shows the average "before and after" results for several performance measures if all three options are implemented. The model results clearly suggest that patient waiting time and thus overall time in the clinic would be reduced. Further, total clinic time (i.e., the time interval over which surgeons see patients) would not be increased. In fact, the model predicts a slight improvement. The reason that total clinic time is not as improved as patient waiting is because the new schedule spreads the patients across the clinic day more evenly. This offsets the benefits due to the surgeons arriving promptly at the start of the clinic and due to the additional x-ray technician. Nonetheless, it appeared that combining the three improvement options would meet the performance objectives of the cast clinic.

The results in Table 2 hold if all improvement options are implemented simultaneously. However, we were concerned that one of the options might be driving the majority of the performance gains that were obtained. Thus we also studied the individual effects of the three options on several performance measures. We ran each of the improvement options individually for the different clinic configurations as separate scenarios for this purpose.

Figure 5 shows the results for total patient time in the clinic and the percentage of patients completing their visits in 60 minutes or less. All three options contribute relatively equally to the reduction in total patient clinic time. However, adding the x-ray technician has a significantly smaller effect on the percentage of patients completing in 60 minutes or less than improved scheduling or ensuring that the surgeons arrive promptly. It is also interesting to note the additive values across options and how they compare to the percentage improvement values in Table 2. Concerning average patient clinic time, there appear to be diminishing returns when all options are added, as the total improvement for the options (50.2%) is less than the sum of

Table 2 Model results: the impact of improvement options (averages for all surgeons and clinic configurations)

	Length of initial wait (min)	Total patient clinic time (min)	X-ray wait (min)	Wait time for surgeon (min)	Clinic end time (hr)	% Patients completed in 60 minutes or less
Model results without improvements	33.42	86.85	36.27	29.97	7.23	40.9%
Model results WITH improvements	4.66	43.26	1.54	16.87	7.07	78.3%
% improvement	86%	50%	96%	44%	2%	92%

the improvement due to the three individual options (61.2%). However, there appears to be a synergistic impact of implementing all three options for the percentage of patients completing in 60 minutes. The improvement percentage due to all three together (91.5%) is significantly greater than the sum of the individual improvement percentages (59.3%). Thus, it appears that combining the options together has a greater effect on the variability of wait times in the clinic than on their average value.

6 Implementation results

As our analysis clearly indicated that each of the improvement options tested was worthwhile, all three options were implemented at the clinic and evaluated using a data collection process similar to that used for the model building phase. Post-implementation data were collected for three surgeons during the period October 2008 to February 2009. Over this period six separate clinic days were used for data collection on 380 patients, for a total of 581 patients.

The overall results averaged across the clinics are shown in Table 3. All measures show significant improvements. Although improvement percentages for three of the five measures were lower than those projected by the model, the average patient time in the clinic dropped from around 90 minutes to under an hour, and percentage improvements for clinic end time and the proportion of patient visits

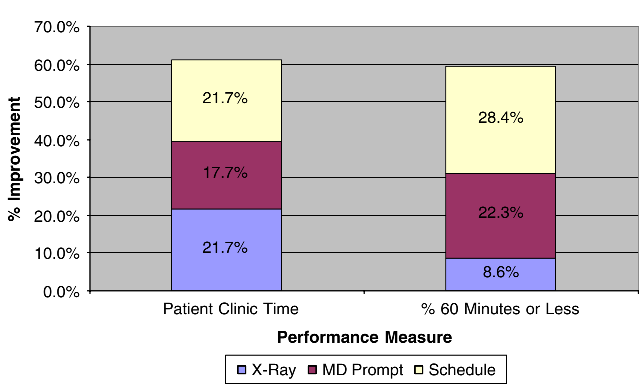

Fig. 5 Main effects % improvement

completed in 60 minutes or less are actually better than what was projected by the model. In addition, the average time a patient was sitting in the waiting room at the start of a visit dropped from more than a half hour to under fifteen minutes,

Figure 6 shows the results for total patient time in the clinic, comparing original performance with model projections and post-implementation results for the three clinic configurations originally considered. The fact that the model projected better performance than actually resulted for the waiting time measures is not entirely surprising. The model assumed perfect adherence to the improvements suggested. In particular, patients' preferences likely required compromising on the planned clinic schedule of 2 patients every 15 minutes which the model assumed, as well as the plan of putting all new patients at the end of the schedule. Furthermore, the times when the first patients were processed suggests the surgeons were not as prompt in arriving as was assumed in the model. Nonetheless, the surgeon arrival times to the clinic were better than they were before the surgeons had been provided with results from modeling that gave evidence of the value of this practice.

One difficulty in trying to make a comparison between the clinic's performance before and after implementation of the improvements is that a number of factors, such as patient mix, were somewhat different in the pre- and post-implementation data. For example, for the post-implementation data collection Surgeon A had individual clinics, while Surgeons B and C had combined clinics. However, for the pre-implementation (i.e., model building) data collection Surgeon B also had an individual clinic day. Regression analysis can be used to control for such unplanned changes that might otherwise obscure the reasons for differences in pre- and post-implementation performance. Table 4 shows the results of such a regression analysis in Stata (StataCorp LP, 2009, version 10.1 for Windows) with total patient time as the dependent variable and a number of independent variables that help to explain the variation in clinic time across patients. The coefficient on the "After" variable, which is set to 0 for the pre-implementation data and 1 for the post- implementation data, indicates that, after controlling for the impact of the

Table 3 Implementation results: comparison of before and after implementation of improvements (averages for all surgeons and clinic configurations)

	Length of initial wait (min)	Total patient clinic time (min)	X-ray wait (min)	Wait time for surgeon (min)	Clinic end time (hr)	% Patients completed in 60 minutes or less
Actual results without improvements	34.5	85.00	35.55	38.46	7.18	26.0%
Actual results WITH improvements	13.3	56.66	10.87	24.87	6.59	62.0%
% improvement	61%	33%	69%	35%	8%	139%

other explanatory variables, there is a statistically significant reduction in patient time in the clinic of approximately twelve minutes per patient on average that can be directly attributed to the improvements made in the clinic. Although this is less than the 30-minute reduction indicated without regression analysis, it is clearly of practical significance.

Results on the other independent variables in Table 4 provide insight into the factors affecting clinic performance and suggest places where future improvements might be made. Patients who are walk-ins experience an 11-minute longer average time in the clinic than other patients. Patients who arrive earlier in the day have a slightly longer wait, probably because surgeons are still arriving a bit late to their clinics. Every patient that is in the clinic when a patient arrives adds about three minutes to that patient's expected time in the clinic, so there is still some congestion in the clinic. Surprisingly, the number of minutes that a patient is early or late to the clinic has no effect on that patient's clinic time, but every additional trip to the examination room or the x-ray adds 15 to 17 minutes to a clinic visit. Finally, it is clear that there is a good deal of variation in how surgeons practice, as a patient seeing Surgeon A or 2 can expect to get through the clinic more than twenty minutes faster than Surgeon C's patients.

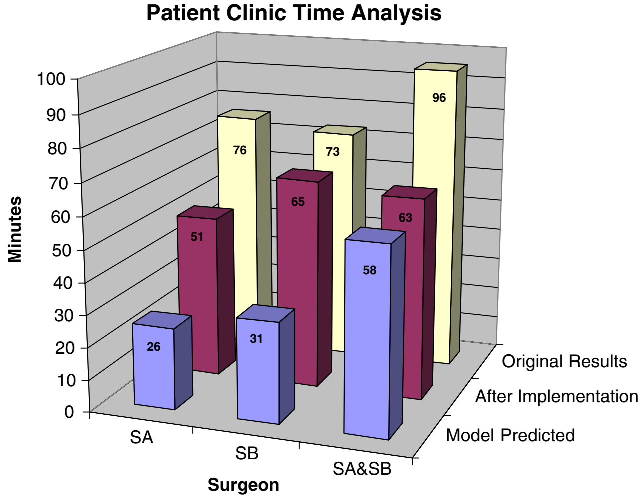

Fig. 6 Comparing original, model, and post-implementation results

7 Conclusions

In this study we report the successful process improvement efforts undertaken at an orthopedic outpatient clinic (cast clinic). The use of discrete event simulation models was shown to be particularly valuable for identifying process improvement alternatives and quantifying potential improvements in performance. This provided motivation to implement the alternatives and also helped in establishing target outcome levels for several key performance measures.

Results from running the model suggested changes to clinic procedures that included adding an x-ray technician staff member, scheduling patients in blocks of 2, 15 minutes apart, and scheduling the new patients who have not been to the clinic at the end of the clinic schedules. Also, the model showed the value of ensuring that surgeons arrived promptly at the start of the clinic sessions. These were all significant changes from original practice that itself was mainly based on tradition rather than careful analysis of the most effective work pattern.

The model projected that these improvements would lead to an average reduction in patient time in the clinic of over 40 minutes. Because no changes occurred in the examination times (i.e., time with providers), this time

Table 4 Regression analysis results on patient clinic time

Variable	Coefficient	*t*	*P*-value
After (0/1)	−11.966	4.98	0.000
Walk-In (0/1)	11.289	3.13	0.002
Hour of Arrival Time (hr)	−1.520	−2.60	0.010
Minutes Early or Late	−.008	−0.23	0.821
Number of Patients Present	2.973	8.92	0.000
Minutes Early or Late	−.008	−0.23	0.821
Number of Visits to Exam Room	17.330	3.77	0.000
Number of Visits to X-ray	15.572	5.19	0.000
Surgeon A (0/1)	−24.786	−8.42	0.000
Surgeon B (0/1)	−21.296	−7.49	0.000
Constant	54.160	7.32	0.000

(n=581; Prob>F=0.00; Adjusted R^2 =0.368) basically represents reduction in patient waiting time. Furthermore, the model predicted that nearly 80% of patients would finish their visits in 60 minutes or less. The actual result after implementing the improvements was a substantial reduction in time in the clinic of about 22 minutes per patient on average. The fact that the model predicted better results than those achieved is likely due to the difficulty in adhering exactly to the improvement policies in practice. It also takes time for a system to fully adapt to process changes, and in our case the majority of the data were collected immediately after implementation. Nonetheless, the performance improvements clearly resulted in less waiting time for patients. When taking into account the differences in the pre- and post-implementation patient groups through regression analysis, and with an average monthly volume of 1000 appointments, the time savings of 12 minutes per patient works out to a total of 200 hours of patient time saved every month.

Implementing the improvement changes over the long term will undoubtedly present a significant challenge. A culture change encouraging doctors to arrive at the clinic on-time, for example, breaks with a common tradition that has led to doctors scheduling meetings and other commitments during the first part of their clinic. Previous observational studies assessing behavior change in activities such as hand hygiene have shown that senior physicians and those in specialty fields are less likely to adopt new practices [24]. Obviously, these trends are worrying to those encouraging new practice behavior.

To ensure the improvements at the Cast Clinic are sustained, we plan to continue to advocate for the implementation of our findings. Scott et al. [25] emphasize the various considerations in cultural change in health systems. Primarily, these strategies focus on ways to adapt current culture rather than re-creating new cultural paradigms. In our setting, this strategy seems particularly applicable as the clinic must fit with the overall goals, traditions, and limitations of the hospital in which it resides. Clear diagnoses of the current problems have already been outlined and will be discussed with all of the appropriate players. Encouraging those players to take ownership of the most relevant changes in their role will also help with motivation and quality assurance. Finally, and perhaps most importantly, we will need to demonstrate the relevance and direct benefit of the changes we propose to all team members so that the specific and overall goals remain clear over the long term. Combined with role-specific education, an on-going audit of clinic performance will help to maintain a culture of sustained improvement in the process of patient care.

Given that the implementation of the improvements required additional resources—in particular, an x-ray technician was added—it is important to consider whether the performance gains were worth this added cost. As discussed in the Introduction, patients do care about waiting time, and a reduction of waits helps to improve patient satisfaction. In addition, because there appears to be a link between patient satisfaction and employee morale [26] there is value to the organization in such system improvements. More satisfied employees will be more productive and will create a virtuous cycle that improves both patient satisfaction and operational performance.

It is hard to quantify the benefit of employee and patient satisfaction in financial terms, and thus future work may entail identifying ways of avoiding adding staff. In particular, the modeling identified some workload imbalances among staff, and it may be possible to cross-train employees in such a way as to maintain the new and improved patient flow without adding staff. Additionally, modeling can be used to show the value of using a central referral system that would balance patient loads more evenly across the clinics. Currently, some clinics are more heavily loaded than others due to patient arrival patterns and surgeon on-call schedules. By balancing patient loads, the effects of variability may be reduced, which would further advance the course of the cast clinic's continuous improvement efforts.

Finally, although our research discusses a specific outpatient clinic setting, we believe the results may be generalizable to other similar healthcare operations. Similar orthopedic clinics in Canada appear to have comparable performance issues [27] and, at least anecdotally, the problems and potential solutions described herein would apply to many high volume outpatient clinics, worldwide.

Acknowledgements We wish to thank the following individuals for their assistance with this research: Taurean Berger, Andrew Hartman, Megan Macadam, and Nolan Sontag. We also thank Bev Campbell and the staff of the Orthopaedic Clinic at the Foothills Medical Center. The third author's research was supported by the Natural Sciences and Engineering Research Council of Canada under Grant No. 239153-05.

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