Desktop Microsimulation: A Tool to Improve Efficiency in the Medical Office Practice

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Abstract: Because the economic crisis in the United States continues to have an impact on healthcare organizations, industry leaders must optimize their decision making. Discrete-event computer simulation is a quality tool with a demonstrated track record of improving the precision of analysis for process redesign. However, the use of simulation to consolidate practices and design efficiencies into an unfinished medical office building was a unique task. A discrete-event computer simulation package was used to model the operations and forecast future results for four orthopedic surgery practices. The scenarios were created to allow an evaluation of the impact of process change on the output variables of exam room utilization, patient queue size, and staff utilization. The model helped with decisions regarding space allocation and efficient exam room use by demonstrating the impact of process changes in patient queues at check-in/out, x-ray, and cast room locations when compared to the status quo model. The analysis impacted decisions on facility layout, patient flow, and staff functions in this newly consolidated practice. Simulation was found to be a useful tool for process redesign and decision making even prior to building occupancy.

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The economic crisis in the United States has increased the pressure to gain efficiency in operations in a number of industries. Healthcare organizations are not immune to these challenges, and forecasted trends suggest that this may persist (Breen, Friedman, Hartman, Kerns, & Schoch, 2009; Evans, 2008; Yokl, 2009). To improve efficiencies in operations, healthcare providers have a range of available options including the centralization of services, the reassignment or reduction of staff, and the employment of process redesign activities to improve workflow efficiency (Goldberg & Petasnick, 2010; Levin & Dickey, 2008).

The ability to optimally select between these competing alternatives requires data analysis. Simulation modeling is an effective analytic tool to guide these important management decisions on increasing organizational efficiencies. Efficiency for the purpose of this research is defined as the ability to do things right (Drucker, 2007) and more specifically as the ability to use fewer resources (i.e., money, employee hours, space, and machine hours) to produce a desired volume and quality of resources (Pande, Neuman, & Cavanagh, 2000). There are three basic approaches to simulation, each with an increasing level of complexity: static spreadsheet models, process simulation, and discrete-event simulation (Kennedy, 2009). Static spreadsheet models can be used to analyze resource optimization; however, when complex, simultaneous processes are under consideration, static models may inadequately reflect the system under study. Process simulation provides analysis of the sequential steps of a flow diagram for maximizing efficiencies. Discrete-event simulation is the most powerful of the three and allows the analysis of changes at discrete time points as triggered by specific process events (Harrell, Ghosh, & Bowden, 2004).

Background

The consolidation of four independent orthopedic practices and their accompanying ancillary services into a single medical office building was the impetus for this study because it provided an opportunity to gain efficiencies, reduce waste, and improve patient flow. This approach, which required the analysis of multiple random variate inputs and outputs, has not been the subject of simulation studies for a practice that is under construction.

Therefore, a study was performed using discrete-event simulation to assist with determining three major goals: (1) to determine that the available space was adequate for clinic operations; (2) to determine that the staff and equipment were appropriately allocated for volume and growth; and (3) to determine the redesign of office processes to enhance patient flow through the clinic.

Approach to Simulation

Step One—Understand the Current Process

After determining a clear set of goals, the team mapped the current processes for each of the decentralized orthopedic practices within the footprint of the new consolidated clinic. Due to high variability in patient arrivals and physician schedules, it was important to model the newly consolidated medical practice over a 5-day period (Monday through Friday) during regular business hours (8 a.m. to 5 p.m.).

Figure 1. Model Layout

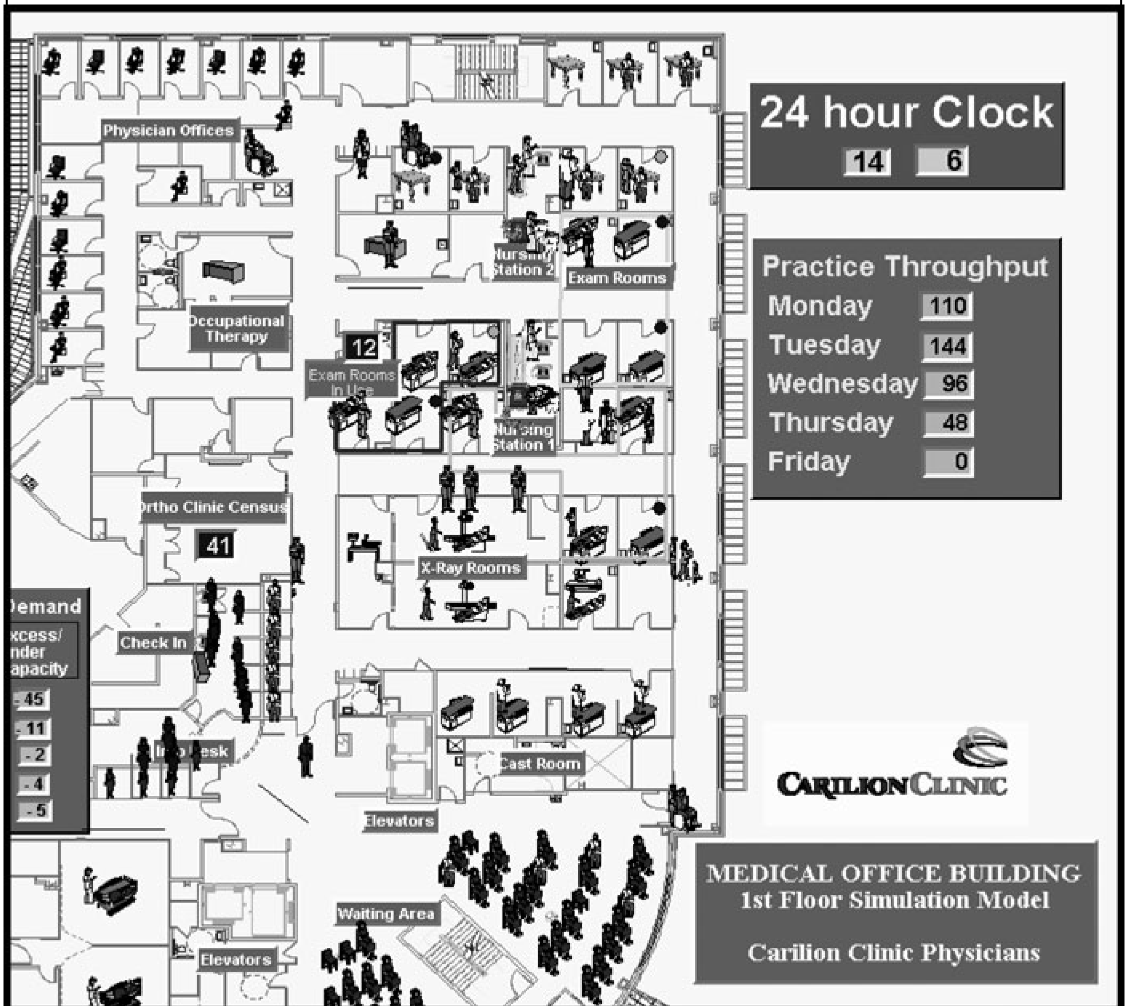

Figure 1 depicts a screen shot of the model captured on Thursday at 2:06 p.m. The patient flow process in the simulation involved routing patients through a series of locations where services were administered by resources (Table 1).

Patients arrived on the floor via elevator and proceeded to an information desk. Next the patient proceeded to one of five check-in/out stations. After check in, patients proceeded to one of the following locations based on a set of user-defined attributes: the cast room, the radiology area, or the waiting room.

From the waiting room, patients were routed to an examination room where they were triaged by a nurse and examined by a provider. If patients required an x-ray or casting prior to the examination, they were routed back to the waiting area prior to moving to an examination room. If a provider ordered an x-ray during the examination, the patient was routed to the radiology center and then to the waiting room prior to returning to the examination room. If a provider ordered casting or occupational therapy, the patient was sent from the examination room to that service prior to returning to the check-in/out stations. Otherwise, at the conclusion of the examination, patients were routed from the exam room to the check-in/out stations. Patient queues were modeled at the following locations: the information desk, the check-in/out stations, the x-ray center, the casting center, and the occupational therapy center.

Table 1. Patient Flow Matrix

Location	Activity Performed	Condition of Activity	Alternate: Routings to Next Location:	Condition of Routing
Information desk	General information	100% of patients	To: check-in	100% of patients
Check-in/check-out	General registration	All base case patients; 15% of scenario patients	To: x-ray	50% of patients identified as needing x-ray prior to exam
	Collect co-pays	56% of patients	Or to: cast room	30% of patients will have cast removal prior to exam
	Register for x-rays	100% of patients requiring x-ray	Or to: waiting room	All arriving patients not going to x-ray or cast room
	Workers comp/FMLA paperwork	25% of patients	Or to: exit	All departing patients
	Check-out	100% of patients		
	Schedule follow-up appt	85% of patients		
Waiting room	No activity	100%	To: exam room	100% of patients
X-ray (Standard)	X-ray	75% of patients routed to x-ray	To: waiting room	100% of patients
X-ray portable	Portable x-ray	25% of patients routed to x-ray	To: waiting room	100% of patients
Cast room	Cast removed	50% of patients routed to cast Rm	To: waiting room	If cast removed
	Cast applied	50% of patients routed to cast Rm	Or to: x-ray	If cast removed and x-ray required
			Or to: OT	If cast applied and requiring OT
			Or to: check-in/out	If cast applied and departing
Exam room	Triaged by nurse	100% of patients	To: x-ray	50% of patients requiring x-ray
	Examined by MLP	All patients except those of certain physicians	Or to: cast room	100% of patients requiring cast application
	Examined by doctor	100% of patients	Or to: OT	32% of hand surgeons' patients
	Suture removal	100% of hand surgeons' patients	Or to: check-in/out	For all patients departing directly from exam room
OT room	Exam by OT	100% of patients routed to OT	Check-in/out	100% of patients departing OT

Step Two—Translate the Process into Simulation Input Components

A simulation study requires that a series of modules are used to frame the design and outline the *who, what, when, where, and how* of the experiment. The software MedModel (ProModel Corp., Orem, UT) allowed for the application of a comprehensive set of input variables necessary to model our medical office building. Table 2 provides the definitions for each of the modules and their relevance to the study (Fitzsimmons & Fitzsimmons, 2004).

Table 2. Components of a Discrete-Event Simulation Study

	Requirements for Simulation Experiments in Healthcare Operations
Entities	Definition: The items processed through the system and that use resources. Represented in this model as: • Patients • Additional activities of front office staff : ■ Paperwork ■ Surgical scheduling
Resources	Definition: A person or item used by an entity to perform an activity. Represented in this model as: • Providers: 9 surgeons, 1 podiatrist, 5 mid-level providers • 7 Nurses assigned direct patient care tasks • 4 Nurses assigned to indirect patient care tasks • 10 Front office staff members • 3 Diagnostic x-ray technicians • 3 Cast technicians • 3 Occupational therapists
Layout and locations	Definitions: Layout: An architectural rendering, built to scale, imported into the software as the background for the animated study (Figure 1). This allows researchers to assign varying speeds of travel for entities and resources. Locations: Fixed points within the model where entities and resources may complete activities at varying time intervals. Locations represented in this model as: • patient entrance and exit points • 1 information desk with 1 information desk queue • 5 check-in/check-out desks with 1 check-in/check-out desk queue • 1 waiting area • 19 exam rooms • 3 x-ray rooms with 1 x-ray room queue • 4 cast rooms with 1 cast room queue • 2 occupational therapy (OT) rooms with 1 OT room queue
Path networks	Definition: The predefined course upon which entities and resources travel between locations. Represented in this model as: The patient and staff flow through 14 hallways between 41 connected locations.
Arrivals	Definition: The initiation of entities into the system. Represented in this model as: Unique arrival cycles per physician per day of week per hour were created that mimicked the volumes and variation found in real patient arrivals. The model simulated a typical work week with patients arriving Monday through Friday from 7:30 a.m. to 5:00 p.m.
Shifts	Definition: Each entity may be assigned to a separate work shift characterized by days of week, start time, break time, and end times. Represented in this model as: Used to account for the high variation in surgeons' clinic schedules. For example, Doctor A might work all day on Mondays and half a day on Thursdays. Therefore, Dr. A would only enter the model on Mondays and Thursdays.
Processing and routing	Definition: The identification of the actions performed by an entity at each location and the instructions given each entity on where to go once all activities as a given location are complete. Represented in this model as: • Processing logic statements that identify randomly produced wait times based on theoretical distributions for physician–patient interaction times. • Routing statements which specify locations where a patient must travel based on predetermined entity attributes (Table 2).

Step Three—Set up Scenarios and Evaluative Criteria

The team designed scenarios that altered input variables to accommodate the measurement of specific outcomes relevant to achievement of three project goals. Four scenarios were developed (Base Case plus three), and eight evaluative criteria were established. Both descriptive statistics and paired *t*-tests at a .05 significance level were used to measure outcomes and determine that scenarios best realized the goals. Tables 3 and 4 outline the project's specific scenarios, evaluative criteria, test methods, and goals.

Step Four—Collect the Data

The estimated volume of patient arrivals was derived from the physician management system database. The mean patient arrivals per day were determined for each provider based upon 6 months of data. Provider and staff shift schedules were obtained from the organization's practice managers. Clinicians, staff, and

Table 3. Identification of Scenarios

Scenario Identification	
Name	**Description**
Base case	The status quo scenario built to include a decentralized registration process and 10 full-time equivalent front office staff combined from the four clinics prior to consolidation
Scenario 2	Modified the Base Case by introducing a centralized registration process into the system but maintaining the front office staffing at 10 full-time equivalents
Scenario 3	Modified Scenario 2 by keeping centralized registration but reducing the front office staff to 7 full-time equivalents
Scenario 4	Modified the Base Case by reducing the casting suite from a four-room configuration to a two-room configuration

Table 4. Identification of Evaluative Criteria

Identification of Evaluative Criteria			
Focus	**Measurement**	**Test**	**Goal**
Exam room utilization	*Utilization rate mean*—The time the exam rooms were occupied divided the time the exam rooms were available over the five-day model run	Meets leaders' criteria of "fully-utilized" = 85%?	1
	Utilization rate max—The highest exam room utilization rate (rooms occupied/rooms available) over the model run	How close does rate get to 85% on peak census days?	1
Front desk queue	*Time in queue*—The mean time patients spend in the queue over the span of the model	Significant as determined by paired *T*-test?	1, 2
	Queue size—The mean size of the queue measured over the course of the model	Significant as determined by paired *T*-test?	1, 2
X-ray queue	*Time in queue*—The mean time each patient spends in the queue waiting for an x-ray during the week	Meets leaders' criteria of <10 Min?	2, 3
	Queue size—The mean size of the queue measured over the course of the simulation	Meets leaders' criteria of <3 patients?	2, 3
Front office productivity	*Idle time*—The mean time front office staff are not in use	Meets leaders' target of 20–30%?	2
Cast room queue	*Queue size*—The mean size of the cast queue measured over the course of the simulation	Significant as determined by paired *T*-test?	3

management were interviewed to identify their job activities, the activity frequency, and activity duration. Radiology utilization data were collected on each provider from automated systems so that the probability of ordering a diagnostic x-ray and an empirical distribution of x-ray procedure types were determined for each provider. Additionally, the average activity time data for each radiologic procedure type were collected from the radiology staff.

Step Five—Build the Model Accounting for Variation and Decision Points

The software allowed incorporation of multifaceted variation found in an orthopedic practice into the model. Model-generated theoretical distributions were fitted to empirical data through goodness of fit tests by means of MedModel's embedded software Stat:Fit (Greer Mountain Software Corp, South Kent, CT). These theoretical distributions were used to assign activity times or probabilities of reoccurring events using MedModel's random number generator.

Theoretical distribution formulas representing activity times were then input into the processing logic of the model. Patient time at check-in/out was a function of the check-in activities that varied for each patient. A provider's decision to order an x-ray was a function of his/her historical ordering patterns. Each physician's x-ray order rate was calculated, and a unique probability for x-ray ordering was then imported into the model for each physician. X-ray procedure time was a function of the type of procedure and whether digital or analogue processing was used. An x-ray procedure distribution profile was determined for each provider, so that during the simulation, if Physician A ordered an x-ray, the duration of the procedure would be randomly selected from a theoretical distribution based on Physician A's empirical profile. A provider's decision to order a cast was determined using the historical probability of applying or removing casts per patient visit. A patient's time in the cast room was a function of category, frequency, and duration of casting procedures. Time in exam room was dependent on the amount of time required for each patient interaction: with the nurse, with the mid-level provider and with the physician.

The number of patient arrivals also varied throughout the day and throughout the week. Thus, the model was built to encompass a 5-day period. Because input data reflect true-life variation, the randomness of the variables results in one simulation replication representing only one of several possible outcomes (ProModel, 2008). Therefore, 50 iterations of the model were run simulating 1 year of operations, thereby assuring that the results were reproducible and were within management's acceptable confidence levels.

Step Six—Verify and Validate

Verification was confirmed by running the simulation in animation mode and insuring that the model worked the way the team intended. Patient movements were observed and counters depicting real-time "queue" values were monitored. Special attention was given to ensure that operating hours, staff activities, treatment times, and building architecture simulated real life.

Two methods were used to validate the model: one prospectively and one retrospectively. Face validity was achieved by allowing the orthopedic practice manager and physicians to view the model in animation mode and validate the type, quantity, and time involved in performing each task. The interviews validated that the model was a reflection of the processes modeled. Although it is difficult to validate a model of a new medical office building, or any system, prior to occupancy, the team requested that the interviewees apply current processes in the futuristic model setting, and sensitivity analyses were performed to adjust the model over a range of inputs.

After the building was occupied and the new system set in motion, the model was compared to the actual system. Empirical data were collected on the turnaround time from patients' exam room entrance time to departure time. The mean empirical turnaround time was compared to the mean computer-generated turnaround time. A z-score test showed no significant differences between the means of the two samples at a .05 significance level, thus validating the model ($p = .63$).

Results

After running the model and collecting statistics, output data were analyzed for answers to the three original research questions. The software was capable of returning statistical output data on measurements of interest to include time series graphs depicting queue sizes. Table 5 represents the results matrix used to analyze output data.

Was the Available Space Adequate for Clinic Operations?

The examination room utilization analysis was important in determining whether or not to allocate more space to providers. The model demonstrated that, with the exception of two clinic sessions when utilization peaked at 83%, excess capacity existed throughout the week under all scenarios. The mean utilization rates for the Base Case, Scenario Two, and Scenario Three were 47%, 50%, and 50%, respectively, demonstrating that regardless of the scenario, average utilization never met leadership's "fully utilized" definition of 85%.

Of additional importance was whether the clinic design included enough check-in/out booths. A study of check-in/out queuing confirmed under which scenarios facility capacity was adequate by estimating at which points queue wait time and queue size expanded beyond acceptable levels. Mean time-in-queue and size-of queue findings were compared among scenarios. Mean time-in-queue for Scenarios Base, Two, and Three were 6.6, 0.5, and 1.0 min, respectively. Adding the preregistration process and reducing staff resulted in a significant decrease in the time-in-queue: (Base vs. Scenario Two: $p < .0001$); (Base vs. Scenario Three: $p < .0001$). Similarly, the mean size-of-queue findings were 4.0 patients, 0.8 patient, and 1.0 patient for Scenarios Base, Two, and Three, respectively, demonstrating significant reductions when compared to the base: (Base vs. Scenario Two: $p < .0001$); (Base vs. Scenario Three: $p < .0001$). Thus, the model demonstrated that enough check-in/out booths were designed provided that either Scenario Two or Three was implemented.

Was the Staff and Equipment Appropriately Allocated for Volume and Growth?

To ensure efficient front office staffing, idle time rate was compared between the Base and Scenarios Two and Three. The Base Case yielded a mean idle rate of 35% for the 10-staff configuration during the 5-day period. With the introduction of a centralized preregistration process, the second scenario increased the idle rate to 46% for the same 10 full-time eqivalents (FTEs). However, combining the same centralized process with a reduction in front office FTEs in Scenario Three reduced the idle rate to 24%. The most efficient front office staffing configuration was achieved during Scenario Three.

Front office staffing allocation was also evaluated using the same mean time-in-queue and mean size-of-queue measurements described two paragraphs earlier. After reviewing the findings, the staff assumptions were modified by reducing staff from 10 to 7, which increased mean time-in-queue for Scenarios Two and Three (0.5 to 1.0 min, respectively) and the size-of-queue findings for Scenarios Two and Three (0.8 patient to 1.0 patient, respectively). In this case, the staffing efficiencies gained were considered worth the negligible increased wait times.

The same mean time-in-queue and mean size-of-queue measurements were applied to the x-ray queue to confirm that the practice x-ray center was adequately equipped. Only two permanent x-ray units were designed into the orthopedic footprint, and it was important that all patients' diagnostic x-ray needs were accommodated there. The mean time-in-queue for Scenarios Base, Two, and Three were 3.8, 6.1, and 6.1 min, respectively. Meanwhile the mean size-of-queue measurements for Scenarios Base, Two, and Three were 1.3 patients, 1.9 patients, and 1.9 patients, respectively. The results confirmed two fixed x-ray machines and one portable x-ray machine had the capacity to meet the demand for services while producing queuing times and sizes well below the acceptable rates (10 min mean wait time; three patients mean in queue).

Could Office Processes be Redesigned to Enhance the Patient Flow through the Clinic?

Scenario Four was added to allow for observation of how a redesign of the occupational therapy center and cast room might have an impact on patient queues. In the original facility plan, the cast room's capacity was limited to two patients, whereas the capacity of the occupational therapy location was four patients. An exchange of locations between the two services produced a significant reduction in the size-of the cast room queue: (Base vs. Scenario Four: $p < .0001$).

Table 5. Results Matrix

Evaluative Criteria	Exam Room Utilization		Check-in/Check-out Queue		x-Ray Queue		Staff Idle Time	Cast Room Queue
Scenario	Utilization Rate Mean Utilization	Utilization Rate Max Utilization	Mean Time in Queue Per Patient	Mean Queue Size Per Model Repetition	Mean Time in Queue Per Patient	Mean Queue Size Per Model Repetition	Mean Idle Rate of Total Front Office Staff	Mean Queue Size Per Model Repetition
1. Base Case No centralized preregistration FO staffing: 10	47%	81%	6.6 min	4.0 patients	3.8 min	1.3 patients	35%	0.7 patients (4 rooms)
2. Scenario 2 Centralized preregistration FO staffing: 10	50%	83%	0.5 min	0.8 patients	6.1 min	1.9 patients	46%	N/A*
3. Scenario 3 Centralized preregistration FO staffing: 7	50%	83%	1.0 min	1.0 patients	6.1 min	1.9 patients	24%	N/A
4. Scenario 4 Reduces cast room from 4-to 2-room configuration	N/A*	N/A	N/A	N/A	N/A	N/A	N/A	2.6 patients (2 rooms)

*N/A indicates only output data relevant to the cast room decision was recorded and included here.

The x-ray queuing results were also important from a process redesign standpoint. If patients were rerouted to an imaging department outside the orthopedic clinic because of a lack of capacity in equipment or personnel, inefficiencies, such as longer cycle time, reduced revenue, and increased paperwork, would be introduced into the system. Providing all basic orthopedic patient ancillary needs (occupational therapy, x-ray, and casting) within the space allocated to the orthopedic clinic was an important goal for clinical care and perceived patient satisfaction.

Discussion

Discrete-event simulation is a useful tool for analyzing and improving healthcare in a variety of ambulatory settings including emergency rooms, specialty practices, and ancillary support services. Several emergency room studies (Hoot et al., 2009; Hung, Whitehouse, O'Neill, & Kissoon, 2007; Khare, Powell, Reinhardt, & Lucenti, 2009) have demonstrated that simulation methods can identify opportunities for improving patient flow and reducing wait times. Computer simulation models were also used prior to facility construction for a multispecialty group practice (Vos, Groothuis, & van Merode, 2007). In the discipline of oncology, simulation was used to demonstrate efficiencies in resource utilization and patient flow (Santibanez, Chow, French, Puterman, & Tyidesley, 2009) and to analyze multiple responses of several patient routings among services involving numerous varying patient attributes and arrival patterns (Matta & Patterson, 2007). No studies were identified that demonstrated the value of discrete-event simulation in planning for the most efficient use of space, staffing, equipment, and patient flow in an unfinished medical office building in which multiple independent clinics were merging.

Desktop microsimulation was used to achieve all three initial research goals and more specifically to inform five major recommendations, which were ultimately implemented, to enhance operations at an unoccupied specialty medical office building. First, the team recommended colocating all four practices on the same wing of the new office building thus preserving 3,000 square feet of clinical space for more efficient uses ($85K per annum cost avoidance). Second, the study confirmed the number of check-in/out stations was adequate only under a centralized preregistration scenario, thereby affirming the necessity for centralization. Third, it was recommended the three radiology units located within the practice serve as the principal source of diagnostic radiology rather than the alternative of sending patients to the hospital-controlled imaging department, thereby reducing patient turnaround time, decreasing patient copayments, and increasing practice reimbursements. Fourth, the study determined the optimal number of front office staff and surgical schedulers (a reduction of three) necessary to process patients under a centralized preregistration scenario. Finally, the model adjusted and affirmed optimal patient flow through the use of both animated visual representations and statistical output functions. Such review allowed leadership to switch cast room and occupational therapy locations and significantly reduce patient wait times.

Computer simulation has many distinct advantages over static decision-making tools. Management can review the impact of decisions in the modeling environment, such as adding or reducing staff or constructing walls, prior to a costly outlay of resources or before staff positions are terminated. Variations in provider and staff scheduling are accounted for by the software and allow an estimation of true resource and location availability. Simulation management provided an element of realism because the team incorporated each provider's practice behavior, to include the probability of ordering procedure-specific radiology studies, from historic data trends. Finally, simulation allows a leader to visualize a system that does not yet exist and make decisions without disrupting operations.

Despite the strengths of computer simulation in this setting, there are a number of limitations. First, the output data and conclusions drawn from the output of computer modeling are only as good as the data inputs. In developing the appropriate arrival numbers for the new practice, historical numbers were used based on a 6-month data collection period. This approach is limited by the accuracy of arrival data and may not account fully for future changes in service demand. To offset this limitation, closer one-on-one discussions were held between the team and physicians, and a sensitivity analysis that increased arrivals by 10–30% throughout the week was added to the model thereby providing additional validation of input estimates. Second, discrete-event simulation is time intensive. Although modeling activities can produce a superior analytic product, there is considerable effort that goes into gathering data, identifying model inputs and outputs, and programming the simulation models. Finally, simulation modeling provides a series of recommendations based upon the analysis that can inform the actual implementation. It is important to assure that reality after "go live" approximates the findings of the model and where there is variation, that the model is updated to replicate reality so that it can be a living tool for process improvement work in the setting under study.

Conclusion

In an environment of economic pressure, it is imperative that decision makers have sufficient analytical tools to inform decisions. Discrete-event simulation uses computer-generated output data and animation to provide a platform for decision making and is recognized as a valuable decision support tool for healthcare leaders seeking operational efficiencies. Through the scenario-building feature, this team was able to analyze data from multiple scenarios, observe the impact on patient queuing, identify exam room utilization and staff idle time, and thereby provide recommendations on the layout, flow, and functions of the staff in this newly consolidated practice.

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