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SIMULATION MODELING TO OPTIMIZE HEALTHCARE DELIVERY IN AN OUTPATIENT CLINIC

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ABSTRACT

This paper presents a comprehensive exploration of an Internal Medicine outpatient clinic practice setting by applying discrete event simulation (DES) modeling. Growing demands on outpatient clinics require greater emphasis on enhancing performance and optimizing resource utilization. Therefore, a data collection plan was designed to capture total patient visit time; including waiting, clinical care, and clinical administrative time. The collected data was fed into a DES model. The model was validated through a statistical comparison with the performance of the real system. Various improvement alternatives were then proposed and investigated through the DES model, such as altering resource allocation, patient rooming and prioritization, and patient volume. For each scenario, key performance indicators of the system, resource utilization metrics, capacity metrics and turnaround time metrics were traced. Findings indicated that targeted improvement scenarios could be applied with 27.5%, 54.8% and 20% enhancement in utilization, capacity and turnaround time respectively.

1 INTRODUCTION

Operational management of outpatient healthcare delivery facilities is an enormously complicated function. Multiple process stakeholders including physicians, residents, nurses, nurse assistants, office managers and patients interact with each other and the other interdependent components of the healthcare delivery system. Other components of the system consist of appointment type, availability of resources and patient arrival rates. A rational decision making procedure to improve the efficiency of the facility to reduce patient waiting time or increase resource utilization can be challenging in such settings.

One possible approach toward effective operational decision making is to apply tools and techniques to reduce the likelihood of errors while pursuing mutually agreeable solutions. Simulation modeling offers extreme flexibility in modeling the real system with a high degree of resemblance and reliability.

Discrete event simulation (DES) has the capability to characterize complex situations, incorporate time dependent events and represent stochastic processes. Simulation in healthcare can facilitate the decision making process for operational and management decisions and empower healthcare teams to observe and analyze the impact of all possible alternatives (Norouzzadeh et al., 2014). Simulation studies can optimize resource utilization, patient scheduling, facility design, health policy decisions, patient throughput, patient flow and system dynamic planning (Klein et al., 1993). In addition, as healthcare continues to become more competitive the ability to assess tradeoffs between service costs and operational delays grows in importance (Benneyan, 1997). DES is a powerful methodology to support decision making in the internal medicine practice due to their workflow complexity and improve the process flow in a safe environment and timely manner.

The primary objective of this study was to identify potential improvement recommendations to optimize the utilization of the clinical exam rooms. Following an initial engineering analysis and adoption of recommended changes, a simulation study was conducted to permit the team to perform additional analysis and expand the objectives to the following three operational parameters: 1) Measure and improve utilization of clinical exam rooms; 2) Measure and improve the physician and medical office assistants (MOA) utilization for patient care; 3) Measure and decrease waiting time and cycle time for patients. Simulation can model and study the behavior of a healthcare delivery setting and evaluate its performance and outcomes for different scenarios. For that reason, simulation is a very powerful visual tool for improving the feasibility and effectiveness of the decision making process. In this study, a multidisciplinary team was specifically charged to develop solution strategies so that the actual implementation of the solutions would be less challenging. The contribution of this research is twofold: 1) reducing the stakeholders resistance to change and improving the implementation success by involving the stakeholders in identifying the problems and determining the alternative scenarios; 2) the methodological contribution of this research is a hybrid framework which integrates discrete event simulation techniques, fast track decision making (FTD) and Change acceleration process (CAP).

The main question addressed in this study is how to make practical improvements in the workflow of the medical practice which benefits all the process stakeholders as well as improving the overall clinical experience for patients. In section 2, applications of DES modeling are reviewed. In section 3, the operations in the internal medicine practice are discussed. In section 4, the structures and steps in development of the simulation model are delineated. In section 5, the results of the simulation modeling and sensitivity analysis are illustrated. Finally, in section 6 the discussion and conclusions are presented.

2 LITERATURE REVIEW AND BACKGROUND

Discrete event simulation has been used frequently to improve productivity and system throughput. Since this hypothesis can be tested with minimal time compared to the actual task after building the primary model, optimal solutions can be identified for complicated processes in a timely and safe manner (Cayirli et al., 2003). Computer simulation can not only empower the teams to evaluate the change in the system by its performance, but it can also evaluate the dynamics of adoption of a new system and its impact on the environment (Anderson 2005). Using simulation in a complex system allows us to study the behavior of the system, understand the interactions within the system and therefore facilitate the decision making process (Norouzzadeh et al., 2014). Literature has shown simulation modeling to be an effective tool used to improve the process or outcomes of healthcare systems. To improve resource utilization and patient throughput simulation studies were focused on work balancing and/or scheduling (Tayloe, et al. 1998; Colli et al., 2007). Since changing the schedule of human resources at the Internal Medicine practice may not be feasible due to budget, rules, and regulations the following is a summary of literature on work balancing (Angelis et al., 2003). An object-oriented DES model was developed to balance the administrative work and direct patient care (Swisher et al., 2002). Simulation has also been applied to optimize the outputs of systems. Ballard and colleagues used the application of DES modeling to optimize an ambulatory care units capacity leveling (Ballard et al., 2006). The model helped the system to maximize the capacity in a surgical unit without increasing staffing resources. Resource allocation to improve outcomes is one of the most common applications of the simulation modeling. Resource allocation for optimal use of facilities for colonoscopy screening has been identified by simulation modeling (Berg et al., 2010). Operational configurations using DES were compared by varying the number of endoscopists, procedure rooms, patient arrival times, and procedure room turnaround time. DES modeling followed by workflow observation has been built and customized to improve healthcare delivery services to minimize costs and waiting times (Alexopoulos et al., 2001; Fetter et al., 1996).

Sometimes the strategies to improve the process can be a result of mathematical modeling or statistical analysis. Simulation modeling can then be applied to evaluate the impact of different improvement scenarios on the outcomes such as resource utilization and patient turnaround time. For example, system dynamics and DES have been integrated to optimize system performance at a very detailed and tactical level (Brailsford et al., 2010). They applied system dynamics as a strategic tool and DES modeling to understand the change in the model at the tactical level.

Patient waiting time and turnaround time are the most tangible metrics to illustrate improvements in a simulation study. Different improvement strategies to reduce long waiting times and delays in a pediatric department have been investigated using simulation modeling (Benneyan, 1997). In their paper, they described the pitfalls of using methodologies such as queuing theory to manage operations by static averages compared to continuous simulation studies.

After an extensive review of the available literature, a decision was made to apply DES modeling to drive effective and efficient improvements.

2.1 Background

The utilization of the clinical exam rooms at the studied Internal Medicine practice was not optimal and the wide variation in utilization had significant impact on the efficiency of the practice as well as patient and staff satisfaction. The focus of this simulation study was to enhance the performance and optimize the resource utilization, capacity and patient turnaround time in the outpatient clinic. An initial industrial engineering analysis of the baseline performance was conducted in the Internal Medicine practice. The results of the statistical analysis recommended the following three improvement strategies, which were implemented by the practice: 1) Standardize all 20 exam rooms for equipment and layout to minimize variation in how patients are roomed for providers. Based upon the study and analysis there were few substantial differences between rooms. Having each room outfitted specifically for an individual physician provided no significant value to the doctor patient visit; 2) Cross-train the Medical Office Assistant (MOA) staff on the workflows and protocols for each practice in order to allow all MOAs to work with any of the office providers; 3) Standardize MOA workflow for patient intake and room preparation to minimize variation in how patients are roomed and how the room is prepped (cleaned) for an incoming patient.

All of the above changes provided a desirable setting for the team to initiate their improvement ideas and explore possible rooming logics. However, due to the criticality of the day to day operations, the team was not ready to take the risk and actually pilot the improvement strategies.

After identifying potential improvements in room utilization, the question became whether further improvements in provider patient interaction time or an increase in the number of patients visits per day could be achieved. Additional measurements and assessments of the clinical tasks of the providers, both in and out of the clinical exam room, were made to determine clinically productive time from potentially wasted time amongst the care team. A simulation study was designed to increase the confidence in effectiveness of the potential identified improvements. In addition, to account for the non-clinical tasks associated during the patient visit time, administrative tasks were measured and factored into the simulation model. The improvements and data collected in both previous studies were used for establishing a baseline scenario in the simulation model for further investigation. Cross trained MOAs, standard rooms, and time distributions for the providers clinical and administrative tasks throughout the patient visit were the inputs for the simulation model.

3 INTERNAL MEDICINE OPERATION OVERVIEW

Mapping the current process in the Internal Medicine practice was helpful to better understand the interactions between the different roles in the process, patient flow and potential bottlenecks impacting the efficiency of the practice. The conceptual process was mapped by a multidisciplinary team including the system engineers, the subject matter experts and frontline providers as illustrated in Figure 1. Resident physicians, post graduate trainees who rotate monthly, provide care to 28% of the scheduled patients, with the other 72% being seen by faculty physicians. Resident physicians' patients are not scheduled for a specific clinician, however, the faculty physicians patients are scheduled for specific clinician. The patients register at the front desk of the practice and wait in the waiting room for the MOA to take them to the assigned exam room. MOA's clean and assign the exam rooms prior to escorting the patients from the waiting room. In their current process, the faculty physician patients have priority to get assigned to an exam room. MOA's perform the patient intake in the exam room and update the electronic health record (EHR) at their desktops after leaving the exam room. There are 20 exam rooms available for patient care. After the MOA leaves the room, the patient waits for the faculty physician or the resident to assess them or perform the medical procedure. After evaluating a patient residents must review their assessment with a faculty member to verify treatment, so their assessment time is longer when compared to faculty physicians with greater variation. After completion of the office visit there are some administrative tasks that need to be performed by either the faculty member or the residents. The administrative tasks include documentation, reviewing the patient record, writing prescriptions, phone calls and referrals. The practice operates 8 hours per day. Although it seems to be a straight-forward process, the complication is partially due to diversity of interactions among interested parties and availability of resources.

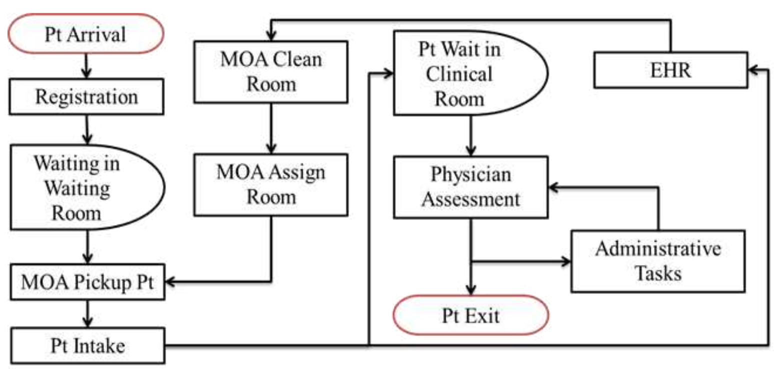

Figure 1: Internal Medicine practice process flow.

4 IMPROVEMENT METHODOLOGY

A conceptual flow was used to develop a baseline simulation model of the clinical practice which represents both faculty and resident practices in their original state. This was validated by statistical comparison with actual data from the practice. In the original model the faculty physicians are assigned to a specific room and a specific MOA based on historic room assignments and MOA-MD relationships. Resident physicians are assigned to a specific MOA and room based on daily assignments by the nursing supervisor. To engage the stakeholders they participated in mapping the conceptual flow and identify the systems bottlenecked by applying FTD tools (Dlugacz, 2004) i.e., brainstorming, affinitizing, prioritizing. A series of statistical analysis in combination with simulation runs was performed to confirm the current bottlenecks and inefficiencies in the process. To manage their expectations and provide them with a better understanding of the process baseline, CAP tools and stakeholder analysis were employed when presenting the preliminary results to the stakeholders (Mento et al., 2002). Different improvement scenarios were discussed in the interdisciplinary team with the stakeholders to be tested for possible selection in the simulation model. The optimal scenario was then implemented and the results were compared to the simulation model to validate the DES model. A summary of the steps and the structure of the methodology are illustrated in Figure 2.

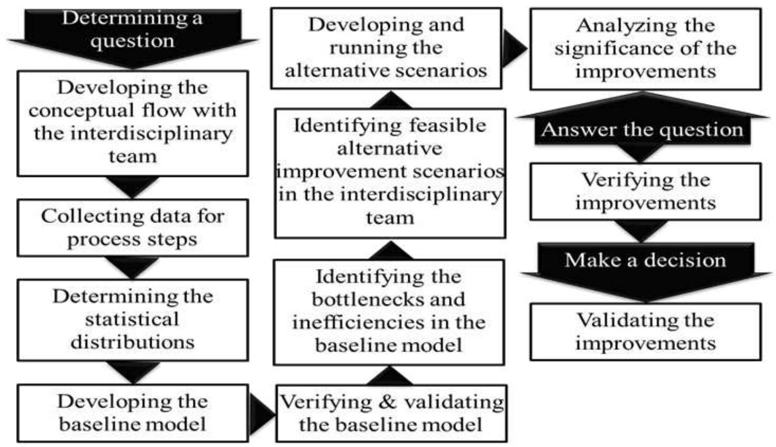

Figure 2: Structure of the methodology in this paper.

4.1 Model Development

Two different alternative rooming scenarios for patients were identified and tested to evaluate the metrics outlined for this study. The alternative scenarios were selected through extensive statistical analysis to identify the bottlenecks along with brainstorming sessions with the content experts. As illustrated in Figure 3, for each scenario, different factors of patient and providers flow in the facility were varied for comparison with the baseline. The impact of the alternative scenarios and factor analysis was evaluated regarding utilization, capacity, and time metrics.

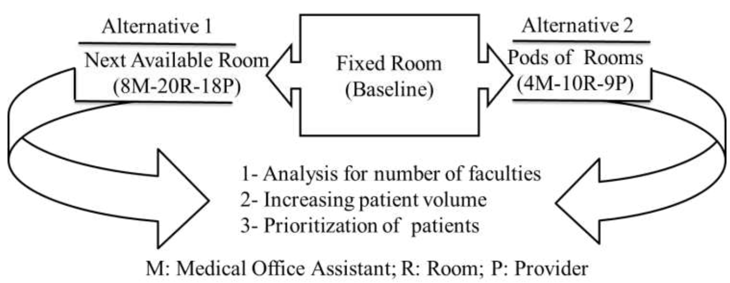

Figure 3: Outline of simulation study.

In the Next Available Room scenario, Figure 3, the next patient in the queue who is waiting in the waiting room, will be assigned randomly to a set, which includes a MOA, room, and resident from all the resources including 8 MOA, 20 rooms, and 12 residents. The patient can also be randomly assigned to an MOA and room and their specific faculty physician if they have an appointment with that faculty physician. The idea of alternative 2 is found on plants where the seeds are formed inside a pod, such as a peapod. they all function the same, but are separated into distinct subsets. The rooms in the facility are logically grouped based on their distance and are termed Pods of rooms. In the Pods model, each of the two hallways in the facility are considered as separate Pods of Rooms with specific MOAs and providers assigned as shown in Figure 4. In this model, the providers are assigned to a Pod according to their room distance from the hallways. The patient will randomly be assigned to a Pod of rooms and a specific MOA and provider for that room. The following hypothesis tests were developed for each of the scenarios:

1- Changes in the number of faculty physicians based upon the range of daily staffing patterns routine in the practice: 4, 6, and 9 faculty physicians were tested.
2- Increases in patient volume by 10% and 25%.
3- Elimination of the priority setting: faculty patients are admitted to exam rooms prior to resident patients regardless of their arrival time. If there are no faculty patients waiting for rooms, resident patients are admitted to exam rooms in the baseline model.

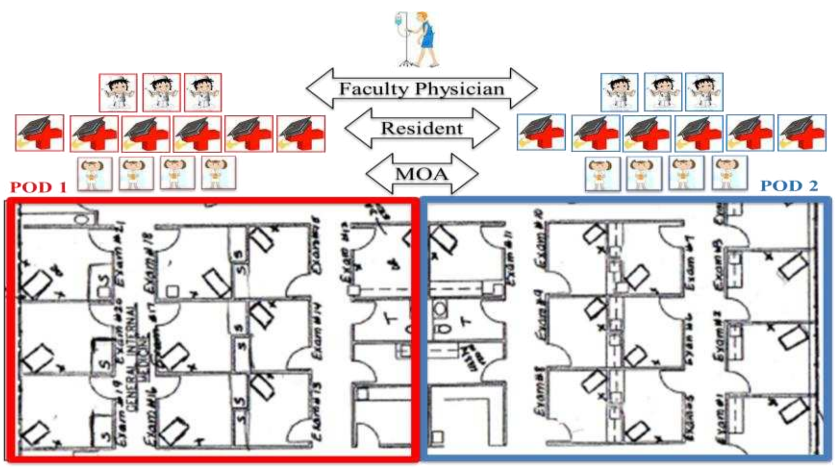

Figure 4: Each of the two hallways in are one Pods of Rooms with specific MOAs and providers.

4.2 Data collection and elements of the outpatient system

Patient flows and resource interactions were observed and the operational data for each step of the process was collected for a month. The data was collected partially through manual forms or extracted from electronic medical records. Once the data collection was complete the data was used to determine the statistical distributions for the simulation model. Preliminary analysis was undertaken using MS-Excel and Minitab. Distribution fitting was carried out in ExtendSim 9.1.

4.2.1 Patients arrival patterns

To avoid the problem with no shows or late arrivals in this model a distribution was fitted to the actual patient arrival times instead of assuming that scheduled arrivals were deterministic. The patient arrival interval was captured during the different times of the day and over the weeks of the data collection month. Figure 5 is the arrival distribution showing the interval between patient arrivals. Using all patients together, the distribution is a Beta distribution, Beta(1,46.2,0.26,2.67), where α equals 0.26, β equals 2.67, location is 1, and range is 46.2.

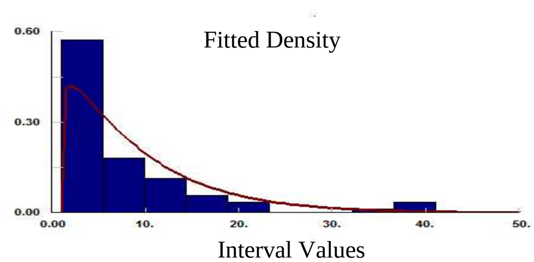

Figure 5: Patient arrival pattern.

4.2.2 Service Times

The DES model was created by dividing the system into patient flow and resource flow, which is restricted by resource capacity. It is assumed in the model that the number of available exam rooms, MOAs, residents and faculty physicians are finite. The average utilization rates were calculated based on utilization of resources over time.

The time distributions for the MOAs to perform the patient setup tasks, clinician medical assessment and administrative tasks are illustrated in Figure 6. ExtendSim 9.1 was applied to fit the distributions using the actual data collected in a period of two months in the internal medicine practice. MOA intake and vital signs assessments on average take the shortest time with the lowest spread, Beta (0, 20.1, 1.29, 3.99) among the clinical tasks. Resident medical assessment on average takes the longest time with the highest spread, Beta (16, 85.1, 2.28, 1.31). However, the shortest times are for patient setup tasks. Model parameters are organized in Table 1.

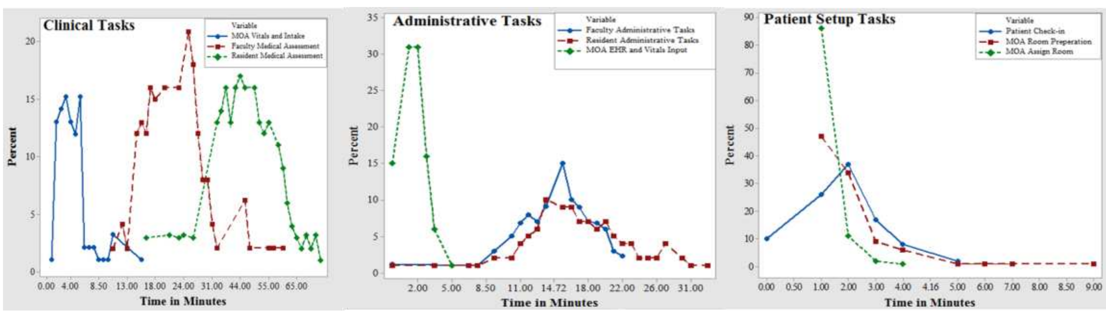

Figure 6: Distributions of duration times for patient setup, clinical, and administrative tasks.

Table 1: Summary of simulation model parameters.

Parameter	Time Distribution
Patient Check-in	Binomial (7,0.293)
MOA Room Preparation	Logarithmic (0.715)
MOA Assign Room	Logarithmic (0.298)
MOA Vital and Intake	Beta (0, 20.1, 1.29, 3.99)
MOA HER and Vitals Input	Triangular (0, 5.52, 1.17)
Faculty Physician Medical Assessment	Beta (0, 65, 1.29, 3.99)
Resident Medical Assessment	Beta (16, 85.1, 2.28, 1.31)
Faculty Physician Administrative Tasks	Beta(3,26.7,2.38,4.95)
Resident Administrative Tasks	Triangular(2,39.2,2)

4.2.3 Waiting Times

Two significant points of patient wait time were identified during the office visit once they registered at the reception desk. First, patients wait for the MOA to escort them from the waiting area to the exam rooms. Finally, they wait for the resident or the faculty physician in the exam rooms. The baseline analysis indicated that patients are waiting in the waiting room on average 25 minutes with a standard deviation equal to 24.7. Waiting in the room for faculty MD is on average 6.7 minutes with a standard deviation equal to 9.1 and for residents is on average 1.6 minutes with a standard deviation equal to 1.5.

5 MODEL RESULTS AND SENSITIVITY ANALYSIS

The numerical results in this study include the baseline scenario, fixed room, and additional scenarios that were constructed by different rooming logics: Next available room and Pods of rooms. Sensitivity analysis for each alternative scenario was done by varying the number of available faculty physicians, patient prioritization logic and patient volume in the practice. Each of the scenarios were simulated for two years, 730 days, to account for the stochastic nature of the process steps. This number of replication created sufficiently tight confidence intervals (95% Confidence Interval) to the mean for reliable decision making. The results reported for each scenario include: 1) mean utilization of resources; 2) the maximum number of patients seen by providers; and 3) mean waiting and turnaround times for faculty and resident patients.

5.1 Operational Performance Evaluations

Operational performance of the practice was evaluated based on the utilization of the resources such as MOAs, rooms, faculty physicians and residents. The Next available room and Pods of rooms scenario results are compared with varying number of faculty, patient prioritization status, and patient volumes as illustrated in Figure 7. Each alternative scenario is coded as scenario type/ priority type/ patient volume increase/ number of faculty. For the sensitivity analysis scenario types are: baseline, next available rooms, and Pods; priority types are: yes, if the faculty physician has priority and no otherwise; patient volume can increase by 0%, 10%, and 25%; number of available faculty can be 4, 6, and 9 based upon the range observed in the actual operation of the practice.

The results of the simulation are ordered based on scenario and then room utilization since it was the primary goal of this project in Figure 7. The positive and steady trend of room utilization in both alternative scenarios indicates the alternatives are improving the room utilization and reducing the variation compared to baseline. Although the increasing trend for MOA, faculty, and resident utilization is not as clear as that for room utilization in Figure 7, because of ordering, their range and averages improved compared to baseline. The next available model with no priority provides the mathematically optimal utilization regardless of the changes in patient volume and number of faculties. The next best scenario Pods model had on average a 2% lower utilization.

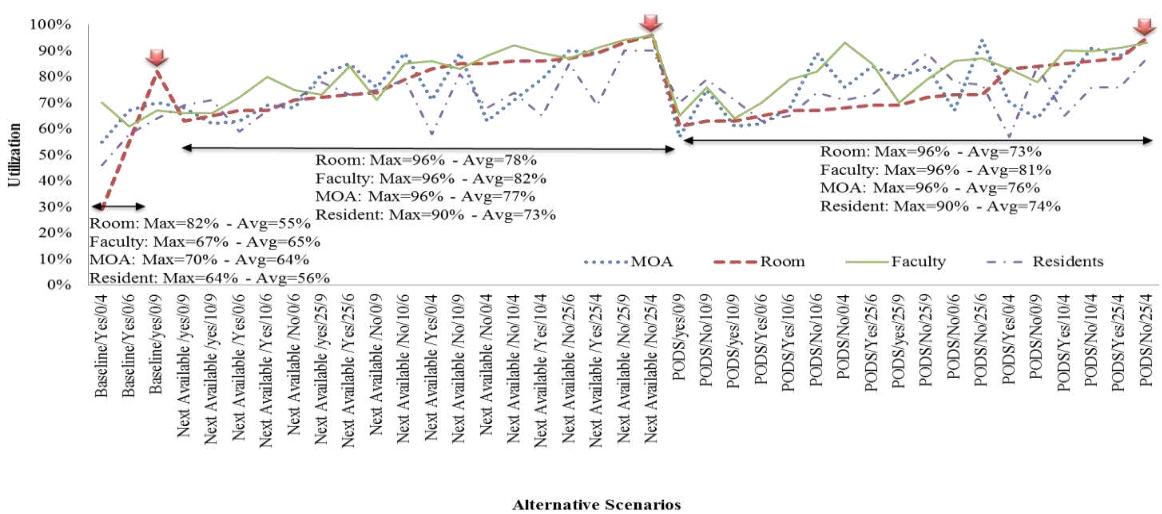

Figure 7: Expected MOA, room, faculty physician, and resident utilization in alternative scenarios.

5.2 Patients Flow Evaluation

Figure 8 illustrates the influence of the alternative scenarios on patient throughput and turn-around-time (TAT). The results of the simulation is ordered based on scenario and then overall turnaround time (TAT) in Figure 8.

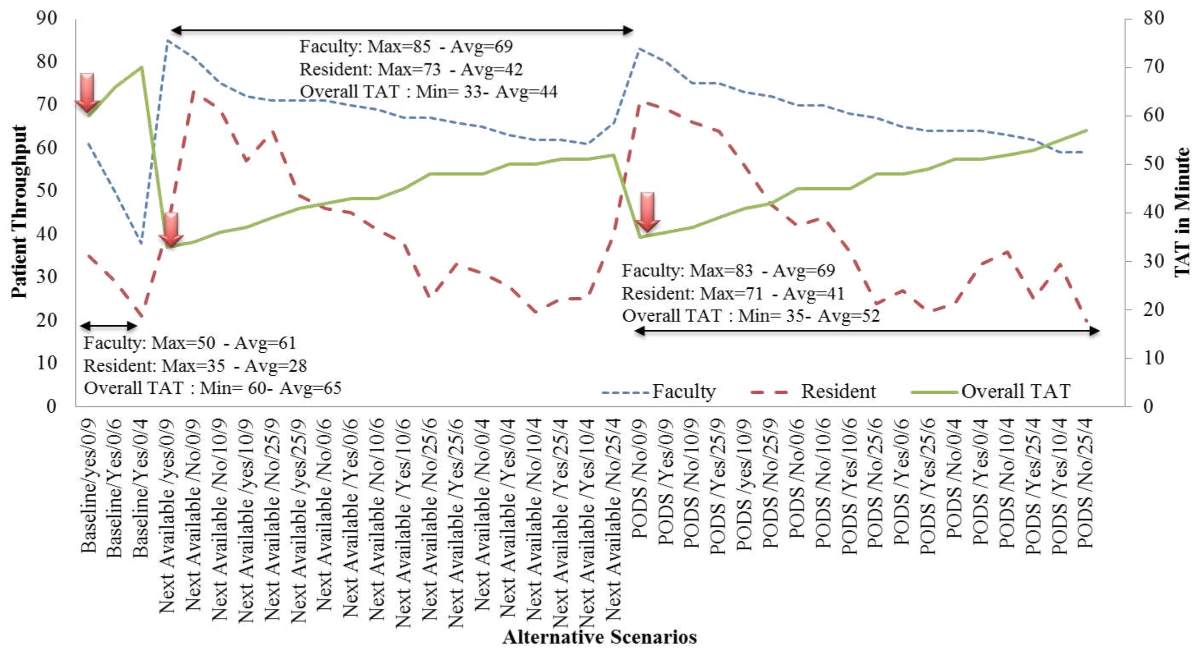

Figure 8: Expected patient throughput for faculty physician and residents and overall TAT.

The interaction of TAT and patient throughput trends indicates that optimum points are improving in both scenarios as well as the average times and throughputs. The next available model with no priority provides the optimal patient throughput and TAT which are 69 faculty patients, 42 resident patients, and 44 minutes respectively. The next best scenario, Pods model, showed an 8 minute increase in average TAT and 1 fewer patient in overall throughput.

5.3 Waiting Time Evaluation

Measurable outcomes of this analysis can be extended to patients' experience as well. The impact of the different scenarios on maximum patient waiting time during their experience in the practice is illustrated in Figure 9.

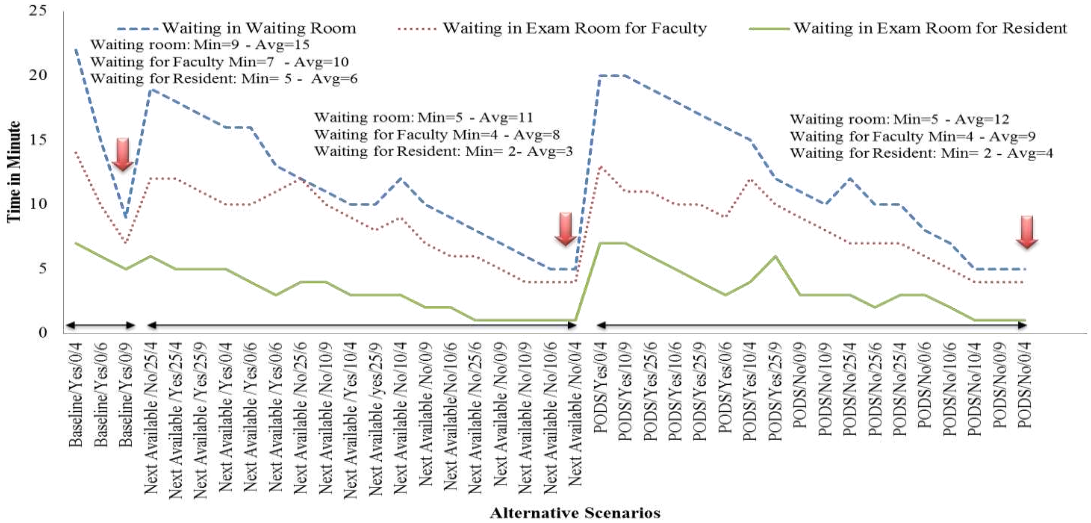

Figure 9: Expected patient waiting time for faculty physician or resident.

The alternative scenarios have a better minimum and average compared to the baseline as illustrated in Figure 9. Next available and Pods Models showed a decrease in the overall waiting time by almost 20%, when no priority existed based upon physician rank.

6 DISCUSSIONS AND CONCLUSIONS

In the first phase, the results of the baseline were compared to both scenarios when the number of faculty and patient volume are changed. The results indicated that the utilization, capacity and time metrics improved in both scenarios compared to baseline. Also, in any alternative model, eliminating rooming priority for faculty patients improved utilization and patient time metrics for both faculty and resident practices. Due to the perceived practicality and lower complexity of the Pods model compared to the Next Available Room, and factoring for the distance between provider office and exam rooms, the Pods model was selected by the practice to be implemented. In the Pods model, the clinicians have to interact with fewer MOAs, 4, and alternate between 10 rooms that are all in the same hallway and visible at once. In addition, the difference in results of the next available model and Pods model were not statistically significant. Simulation results illustrated that by implementing the Pods model room utilization can be improved from 29-82% to 60-86%, decreasing the variation in room utilization by 50%. The results of the Pods model without an additional increase in patient volume is shown in Table 2, where the priority is removed for the faculty patients and the MOA picks the next available patient and assigns a room.

Table 2: Baseline and Pods scenario comparison with no priority for faculty patients.

Metrics	Baseline Average	PodS	Improvement Percentage
MOA Utilization	64.2%	69%	7.48%
Room Utilization	55.2%	75%	35.87%
Faculty Utilization	66.8%	86%	28.74%
Resident Utilization	56.5%	78%	38.05%
Overall Throughput	80 Patient	124 Patient	54.81%
Overall TAT	65 (30.12)*	52 (21)	20%

*Average (Standard Deviation)

As shown in Table 2, all the metrics improved by removing the patient priority variable. Simulation modeling allowed the team to test and evaluate 39 alternative improvement scenarios and select the optimum setting in a safe virtual environment which exactly replicates the real system. The optimum scenario was then chosen based on the improvements in utilization, capacity and time metrics in combination with the feasibility of implementing that scenario.

The Pods model with no priority was implemented in the Internal Medicine outpatient clinic practice and post improvement data was collected to validate the model, as shown in Table 3.

Table 3: Validation of the simulation model.

Metrics in minutes	Baseline Data	Simulation results	Implemented Results	Simulation vs Actual Results P-Value
Overall Patient Waiting time	30 (26.32)	21.8 (11.8)	24 (15)	0.18
Overall TAT	65 (30)	52(21)	52 (24)	1.00

Results of the post improvement data analysis indicated a 20% decrease in the overall patient waiting time and turnaround time. Based on the simulation results, improvements in patient throughput and turnaround time lead to improvement in resource utilization. MOA, room, faculty, and resident utilization improved by 7.5%, 35.9%, 28.7%, and 38.1% respectively. Anecdotal feedback from the practice demonstrated improved employee satisfaction as well. The proposed hybrid research framework empowers the team to engage stakeholders in the improvement process and manage their expectation to facilitate implementation of optimal solution.

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