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SIMULATION MODELING COUPLED WITH A STAKEHOLDER PARTNERSHIP IN AN OUTPATIENT PRACTICE TO OPTIMIZE OPERATIONAL DECISIONS

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Abstract

There is tremendous potential for discrete event simulation to be utilized as a primary resource to aid critical decision-making throughout the healthcare industry [4]. Due to the inherent complexity within this domain, successful buy-in is highly dependent on the partnership that exists between the system engineers and stakeholders. This study uses an adaptive resource modelling approach coupled with a key partnership to uncover the hidden truths within an outpatient endocrinology practice. Key performance indicators were traced to enhance system performance and optimize resource utilization. Based on the findings various improvement scenarios were proposed such as modifying resource scheduling, patient volume and resource capacity. Ultimately, the optimal improvement option presented a 30.7%, 8.5% and 46% improvement in wait time, provider efficiency and patient throughput, respectively.

Key Words: discrete event simulation, modelling, healthcare

Introduction

The healthcare industry continues to face increased pressure to provide quality care at low costs [4]. Due to the competitive nature of this industry, critical decision-making has become a fundamental driver to succeed. Simulation has the power to aid critical decision-making by allowing key process parameters to be altered providing healthcare professionals with the opportunity to analyze and observe changes within the system. The extreme flexibility offered by simulation makes it possible to test a multitude of different scenarios on a model of the real system in a safe cost effective environment.

In order to achieve the vision of embedding simulation into the toolkit of critical decision-making in healthcare, a partnership must be formed between process stakeholders and the system engineers. Obtaining buy-in is an essential component in order to reach mutually agreeable solutions and long-term simulation reliance.

The setting of this study was in an outpatient endocrinology practice where a partnership between the multidisciplinary team of the outpatient clinic and external system engineers worked together utilizing an adaptive resource modelling approach to achieve three primary objectives: 1) Measure and reduce waiting time for patients 2) Measure and improve physician and medical office assistants (MOA) utilization and 3) Measure and improve practice capacity. The contributions of this research are as follows: 1) Leveraging a partnership approach to redirect stakeholder perception of bottlenecks resulting in accurate and effective decision-making and 2) Using an adaptive resource modelling framework to model dynamic resource schedules for day to day operations.

The remainder of this study is organized as follows: A summary of existing literature is discussed in Section 2. The background of this simulation study and the methodology are explained in Section 3 and Section 4, respectively. The various improvement scenarios are described in Section 5. Lastly, Section 6 presents the discussion and conclusion.

Literature Review

As a result of the growing demands placed on the healthcare industry the need to enhance system performance and optimize resource utilization has been placed on the forefront of critical decision-making. Through traditional decision making conclusions are drawn based simply on averages and perceptions whereas decision making using simulation accounts for variability within a system [9]. As simulation software has become more sophisticated there has been an

Increase in opportunities to model new and more complex systems allowing decision makers to quickly determine optimal conditions [5]. Simulation can be used as a tool to account for variability based on capacity constraints. For example, simulation was used to model the relationships between the emergency department (ED) and an inpatient unit and analyze the impact overcrowding in the ED had on the system [8]. In this current study variability was accounted for by collecting data for different type of patients, different days of the week and hours of the day.

Scheduling is another area of focus within the realm of healthcare which can help decision makers optimizes scheduling for operating rooms, resources or patient appointments. Simulation and optimization were used to find the optimal balance between new and existing patients for an outpatient clinic taking into consideration a variety of variables such as no-show rates, walk-ins and appointment types [10]. Similarly, simulation was used to help manage appointment schedules for a primary care practice factoring in stochastic service times for care takers as well as the different appointment types [7]. Although scheduling was not a focus of this current study experimentation was performed to determine optimal allocation of resources in the practice.

Simulation has been applied to a variety of different applications within the healthcare domain contributing to the vast literature that exists. Constantly growing, there are nearly 200,000 journal papers that can be found on health care delivery processes [3]. For example, simulation has been utilized to plan for the potential outbreak of contagious diseases [12]. Additionally, one particular study focused on how changes in a hospital's bed and resource capacity impact patient flow as well as downstream and upstream units [9]. This current study focused on using simulation to model the care delivery process for an outpatient endocrinology practice.

Despite the vast literature that is available healthcare professionals are slow to adopt modelling and simulation as a primary tool to aid decision making. Specifically related to healthcare, only 8% of the existing literature represents "real problem-solving" and only 5.3% of papers describe a real model implementation [3]. In order to make simulation and modelling an established part of the managerial decision-making process in healthcare, literature alludes to the vital role stakeholders have throughout the modelling process. One study argues that to get the physician community to buy into simulation they must first understand that modeling can accurately reflect the current state and then be shown changes in the model's current state can demonstrate results they would expect to see [3]. Generating this clinical comfort and involving stakeholders throughout the modeling process is a critical factor in successful buy-in [1]. One study incorporated fast track decision making and change acceleration process to reduce the stakeholders' resistance to change which ultimately led to a successful model implementation [6]. This study further illustrates how important obtaining stakeholder buy-in is to achieving success in using simulation as a tool to aid critical decision- making in healthcare.

Based on the literature review, simulation was utilized as a real problem-solving tool to provide healthcare decision-makers in an outpatient endocrinology practice with the knowledge and insight to make appropriate decisions. Furthermore, involving key stakeholders throughout the modelling process was incorporated into the methodology to mitigate resistance and obtain buy-in.

Background

The outpatient endocrinology practice is a complex integrated system that encompasses many key stakeholders including physicians, nurse educators, bone density technicians, medical office assistants (MOAs), phlebotomists and clerical staff. As a result of the operational inefficiencies within the practice patients were experiencing longer than desired waiting times. Stakeholders expressed three major points of patient waiting throughout the process including in the waiting area, in the exam room before treatment and waiting for the internal labs to be drawn. These process challenges and inefficiencies were impacting patient satisfaction scores, staff satisfaction, and the community's perception of care delivery.

Conceptual Process Flow

A detailed process map was developed with the key stakeholders involved in the process to better understand the overall process flow at baseline. The process mapping session included system engineers, nurse educators, and a bone density technician, MOAs, a phlebotomist, clerical staff and managerial staff. A conceptual overview of the process flow is illustrated in Figure 1. When patients arrive to the practice they get registered for their appointment by the clerical staff. Once they sign in, signifying registration is completed, patients wait in the waiting area until they are called back to the exam room. MOAs were assigned to specific providers for each day. The assigned MOA will meet the patient in the waiting area and bring them to the exam room. There are 10 exam rooms in total with two exam rooms assigned to each provider. Typically there were no more than 5 providers in the practice at once, however,

Stakeholders stated potential growth in the future. Once the patient is in the exam room, the MOA will perform the patient intake and document this information in their electronic medical record. Following the patient intake the patient has the potential to wait in the exam room for the provider. The provider will then enter the exam room to treat the patient. In efforts to not infringe on providers' clinical freedom the clinical aspects related to the treatment process were treated as a black box. Thus only focusing on the conceptual process which was described by managerial staff and later validated by the providers. After the provider leaves the exam room the patient will be seen for any ancillary services such as diabetes education or bone density testing, if needed. In addition, if labs need to be drawn the patient may wait, otherwise the patient will check-out. This current process flow was incorporated into the model logic.

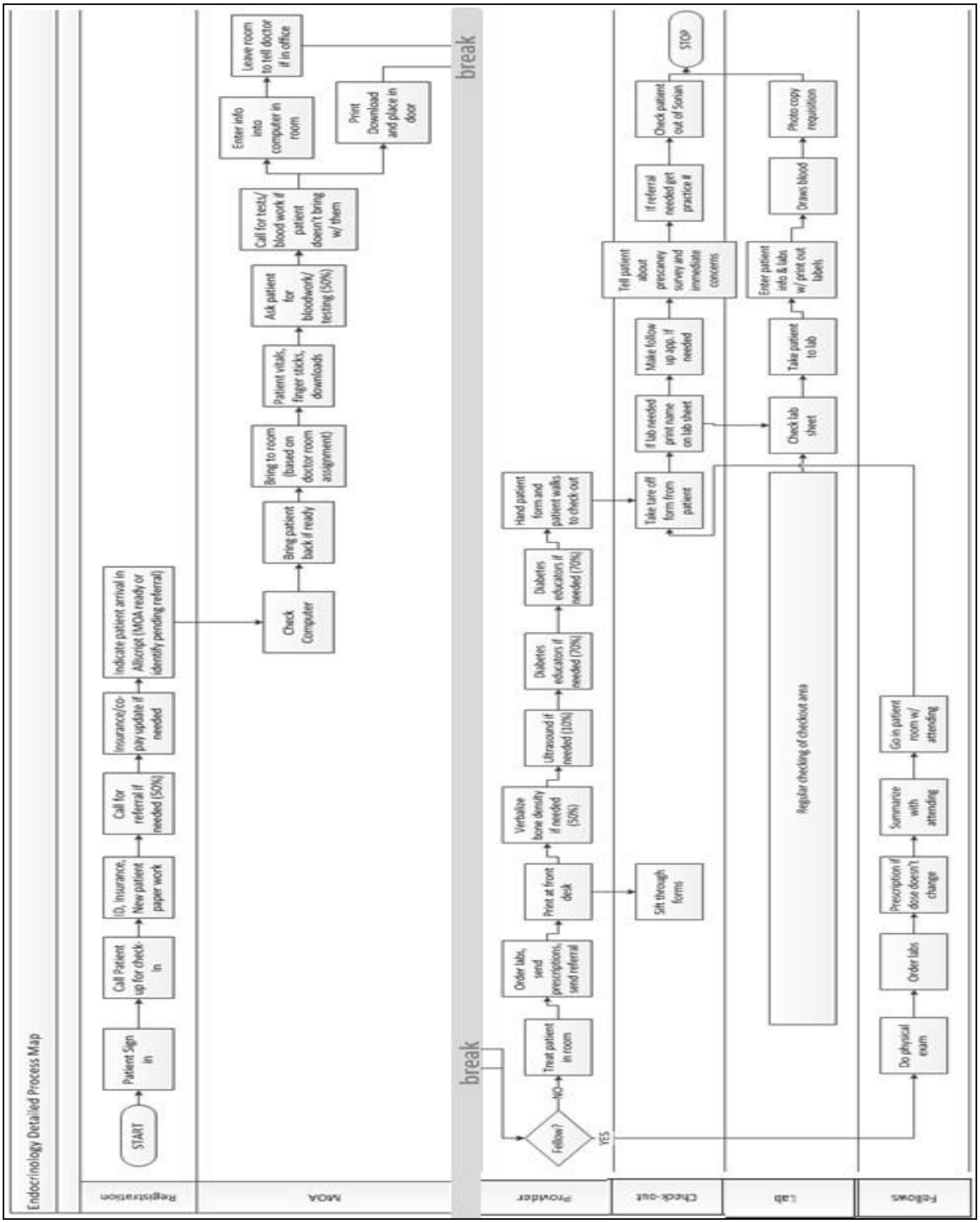


Figure 1: Endocrinology Process Flow

Methodology

A three phase approach was utilized to model the endocrinology outpatient practice as shown in Figure 2. Key stakeholders were involved throughout each phase developing a partnership between stakeholders and system engineers. Phase one consisted of mapping the conceptual process flow, discussing the necessary data and finally collecting the data. Both system engineers and stakeholders were involved in mapping the conceptual process flow as well as discussing the data needed and its availability. Data collection was the responsibility of the stakeholders. Before moving on to the next phase, system engineers assured all phase deliverables were met. Phase two included statistical distribution fitting of data and developing of the baseline model completed by the system engineers. Model verification and validation was a partnership between system engineers and stakeholders to obtain both buy-in and trust that the model was an accurate representation of the actual process. Following verification and validation the system was analyzed to identify bottlenecks and process inefficiencies. Finally, in phase three the system engineers worked together with the stakeholders to come up with multiple test scenarios for possible improvements. System engineers than tested the alternative scenarios and analyzed the impact each one had on the system. All alternative scenarios with their respected impact were presented to the stakeholders, ultimately leaving the decision up to them as to which scenario to pilot for improvement. The discrete event simulation model was developed using Extends 9.2.

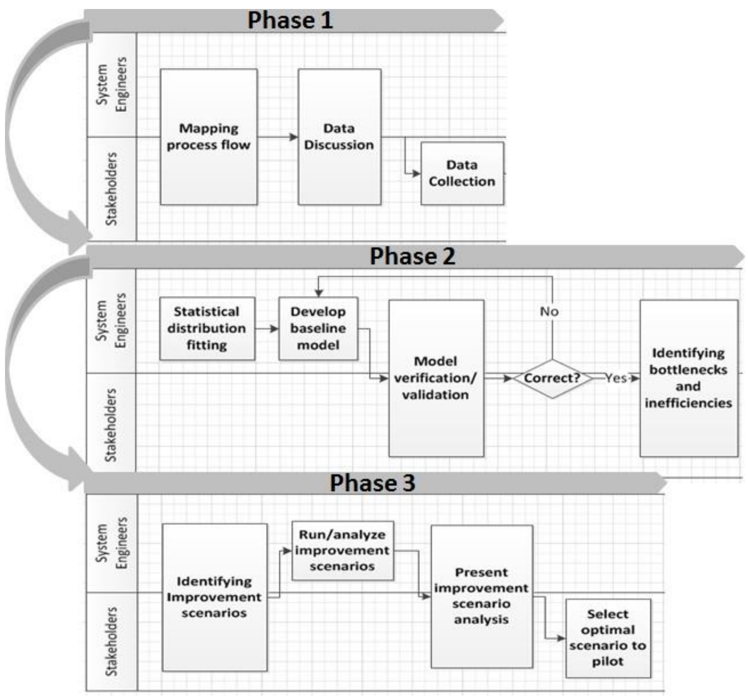


Figure 2: Methodology

Data Collection

Key process metrics were collected to understand patient flow and resource interactions using an extensive manual data collection approach. All key stakeholders were involved including physicians, nurse educators, bone density technicians, phlebotomist, MOAs and clerical staff. The data collection period was for one month to ensure the data was adequate and representative of the current process. The data was then used for preliminary analysis and statistical distribution fitting.

Data Analysis Distribution Fitting

Preliminary data analysis resulted in patients waiting in the waiting room on average 26 minutes with a standard deviation of 19 minutes, waiting in the exam room before treatment on average 9 minutes with a standard deviation of 9 minutes and patients waiting for labs to be drawn on average 6 minutes with a standard deviation of 5 minutes. The Center for Medicare and Medicaid Services (CMS) benchmark for the time patients should wait before their scheduled appointment is an average of 15 minutes. The clinic is operating at a 46% defect rate justifying the primary focus of the simulation study to reduce the time patients wait in the waiting area before their scheduled appointment. Taking into account the two points of waiting before the patient see's their provider, patients wait on average 34 minutes. Interestingly enough the preliminary data analysis did not support the stakeholders original hypothesis that one of the major bottlenecks within the process was the lab. System engineers developed a new hypothesis that the lab was not a bottleneck. The lab process was still incorporated into the model as it was perceived to be a major pain point by the stakeholders. Simulation was used as a visual aid to demonstrate to stakeholders the new hypothesis that the lab was not a bottleneck at all.

Statistical distributions were fit for the key process steps within the practice which included registration, patient intake, provider treatment, nurse educator assessment, bone density testing, drawing of labs and patient check-out. Table 1 shows the distributions that were deemed best fits for their corresponding process step. The intake process performed by the MOA was the shortest process step taking on average 3 minutes with a standard deviation of 3 minutes. After fitting the raw data into a distribution the best fit for this process was a Lognormal with μ equal to 0.68, σ equal to 0.603 and a location equal to 0.536. The longest process step was the patient treatment time with an average of 22 minutes and a standard deviation of 13 minutes. Feeding this raw data into a distribution yielded a best fit of Log-Logistic with a α equal to 3.35, β equal to 16.3 and location equal to 2.04.

Table 1: Statistical Distributions

Process Step	Distribution
Registration	Weibull (1.94, 1.34, 25.8)
Intake	Lognormal(0.536, 0.68, 0.603)
Treatment	Log-Logistic(2.04,3.35,16.3)
Bone Density	Pearson 5 (-12.8, 36, 950)
Diabetes Educator	Triangular(3, 1, 4)
Check-out	Pearson 6 (0, 0.729, 16.9, 4.96)
Lab Drawn	Inverse Gaussian (-0.623, 24.3, 3.45)

Providers and MOAs were dynamically scheduled throughout the day as well as throughout the week. The variability within the scheduling of providers and MOAs are shown in Figure 3. In total there are ten providers that account for a total of five FTEs as providers do not primarily reside in this practice. As a result patients are scheduled based on provider availability, therefore, providers are only in the practice to see patients. At any given hour there are no more than five providers in the practice with some exceptions due to patient complications. MOA scheduling is more consistent when comparing each day with each other. For example, Monday through Thursday are the same whereas Friday differs. However, the variability throughout each hour of the day remains. This fluctuation in the number of resources available per hour per day was

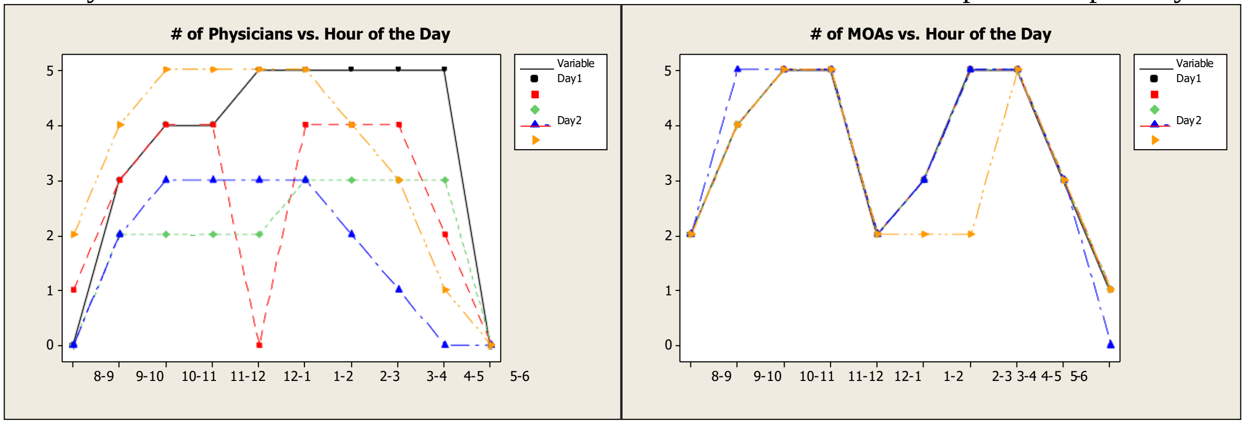


Figure 3: Provider and MOA Scheduling

The adaptive resource scheduling approach accounted for the dynamic changes in resource staffing throughout each hour of the day and all days of the week. The number of physicians, the number of MOAs and the number of rooms available, dynamically changed throughout the simulation run. Patient arrivals are not deterministic as there is the potential for patients to no-show and arrive late to their appointment. For this reason patient arrival patterns were fit to distributions. Actual patient arrival patterns per day are shown in Figure 4 where it is evident that a sole distribution fitting is not appropriate.

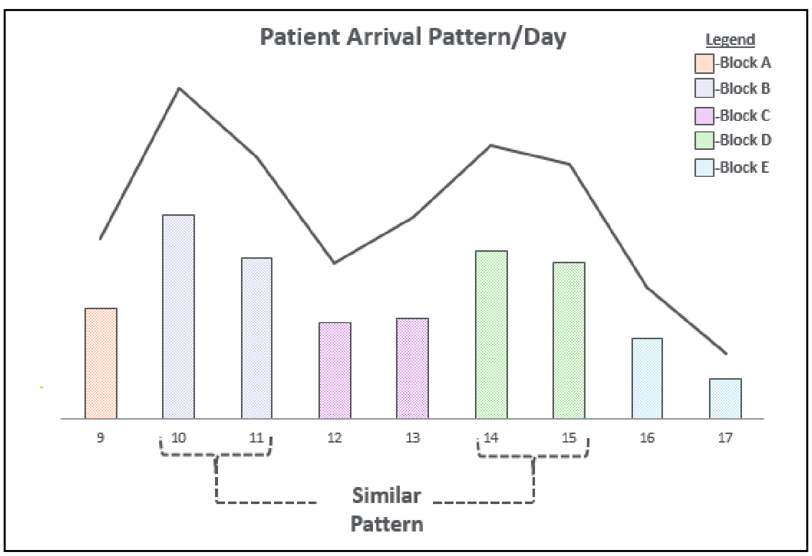


Figure 4: Patient Arrival Pattern per Day

Specifically, patient arrivals were separated into five different time blocks each block accounting for two hours of the work day as shown in Figure 5. The raw data was stratified into these five time blocks fitting distributions for patient arrivals within each block. The five specific time blocks, A, B, C, D, E, were defined from 8am-10am, 10am-12pm, 12pm-2pm, 2pm-4pm and 4pm-6pm, respectively. The patient arrival patterns differed within each block, however, 10am-12pm and 2pm-4pm were peak appointment times for the practice and followed the same distribution. Figure 5 shows the five best fit distributions that were used for each of the five time blocks.

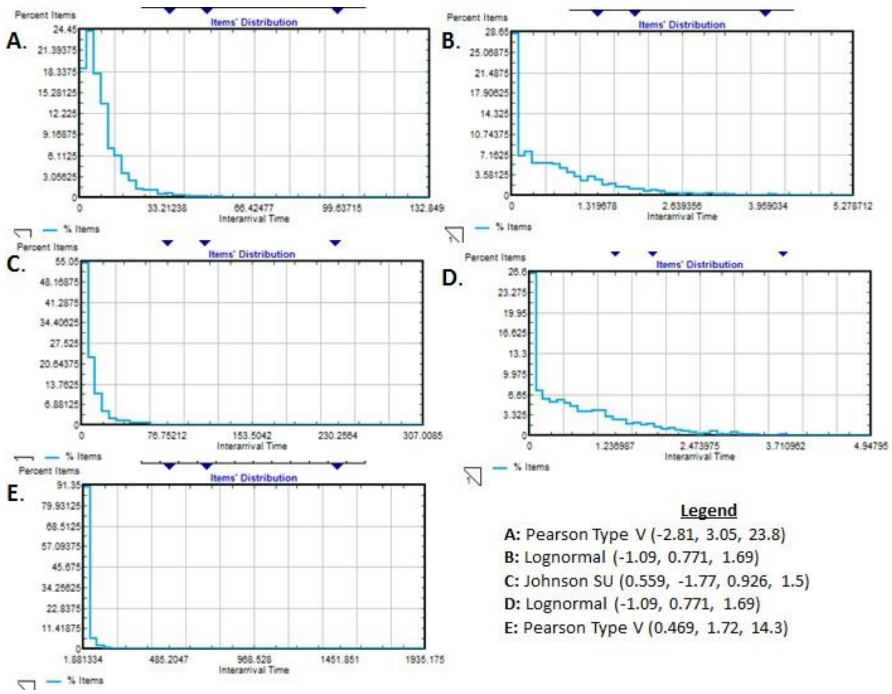


Figure 5: Inter-arrival Distributions

Model Validation

Baseline model results were compared against the raw data that was captured through the manual data collection. Two points of model validation were performed to see if the model was an accurate representation of the actual process. The overall turnaround time and the time patients waited in the waiting room were used to validate the model using a Moods Median statistical test. Table 2 shows the comparison between the actual data and the simulation model results concluding that there was no statistical difference between the two.

Table 2: Model Validation

Validation Points	Baseline Data	Simulation Results	p-value
Patient Wait Time in Waiting Room	22.0 Minutes	26.0 Minutes	0.294
Overall Turnaround Time	64.0 Minutes	64.9 minutes	0.865

Key parameters were captured to understand the system's baseline performance including resource utilization, waiting times and the overall throughput of the process. Table 3 shows the initial baseline results specifically capturing room, physician and MOA utilization. As well as the average time patient entities waited in the waiting room and in the exam room before treatment. Finally, the overall system throughput was captured.

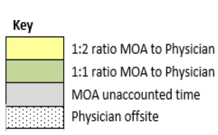
Table 3: Baseline Results

Metrics	Baseline Results
Room Utilization	87%
Physician Utilization	83%
MOA Utilization	23%
Patient Wait in Waiting Room	26(21) Minutes
Patient Wait in Exam Room	9(7) Minutes
Overall Throughput	306 patients/week

*Average(Standard Deviation)

System engineers and key stakeholders met to go over the baseline model results. Going over the model validation and having had the model logic and flow previously verified and confirmed by key stakeholders, they were having trouble believing the baseline results were an accurate representation of their current process. The one aspect that they found hard to believe was that MOA utilization was only 23%. Knowing the importance of obtaining stakeholder buy- in and confirmation that the model is in fact an accurate representation of their current process, system engineers worked with key stakeholders to dig deeper into the MOA workflow specifically. An additional manual data collection was done in order to capture administrative tasks that the MOAs may be doing when they are not performing the patient intake. As a result of the data collection findings showed that MOAs were spending on average only 7 minutes making phone calls, 10 minutes performing chart reviews and 8 minutes scanning documents per day. Furthermore, a master schedule was developed encompassing both provider and MOA scheduling. Figure 6 shows a snapshot of this master schedule for three days of the week. The green boxes represent times when one MOA is working with only one physician's patients. The yellow boxes represent times when one MOA is working with two physician's patients. The grey boxes represent unaccounted time as the MOA is not working directly with any physician's patients. Based on the initial data collection MOAs spend on average 3 minutes with a standard deviation of 3 minutes performing the patient intake. Therefore, during green and yellow blocks depicted in the master schedule below there is still more than enough time within that patients appointment to scan necessary documentation, review charts for the next patient and make any phone calls needed.

System engineers met with stakeholders and presented their findings and with the master schedule visualization stakeholders had an "ah-ha" moment. The master schedule was compiled directly from the combination of actual physician and MOA schedules. When investigating further by asking stakeholders what tasks do the MOAs do during the grey blocked times there was no clear answer as it became evident that the 23% utilization the baseline model provided was in fact an accurate representation of their current workflow. With this realization stakeholders knew this was an issue and were ready to test scenarios to improve their process.



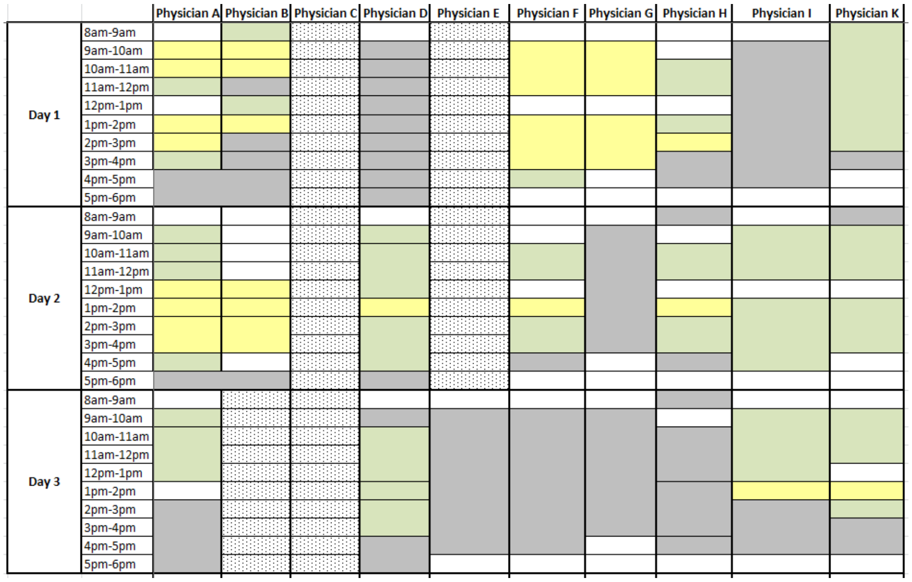


Figure 6: Provider and MOA Master Schedule

Improvement Scenarios

Key performance indicators were traced for each tested scenario in order to compare improvements to baseline. Utilization, waiting time and throughput were the three performance metrics that were analyzed. A variety of improvement scenarios were tested by changing key model inputs and parameters including increasing physician clinical capacity, patient volume and patient scheduling. The top three scenarios that presented the biggest improvements are shown in Table 4. Scenario 1 added 40 physician clinical hours, increased patient volume by 25% and proportionately aligned patient schedules with physician schedules. Scenario 2 focused on proportionately aligning patient schedules with physician schedules. Finally, Scenario 3 increased physician clinical capacity to 40 hours as well as increased patient volume by 25%.

Table 4: Improvement Scenarios

Scenario	Room Utilization	Physician Utilization	MOA Utilization	Waiting in Waiting Room	Waiting in Exam Room	Throughput per Week
1	93%	90%	53%	18(18)Minutes	3(5)Minutes	447
2	86%	87%	41%	16(10)Minutes	5(6)Minutes	328
3	86%	73%	48%	26(27)Minutes	4(5)Minutes	346

Discussion and Conclusion

The greatest opportunity for improvement for the practice was to modify the scheduling which is a direct result of their dynamic scheduling of resources. The fluctuation in the number of resources per hour created an unstable process and added chaos into the system. By proportionately aligning patient schedules with physician schedules, increasing provider clinical hours by 40 hours per week and increasing patient volume by 25%, the practice will see an increase in their resource utilization by 6.8%, 8.5%, 130% for room, physician and MOAs respectively. In addition, they will see a decrease in average waiting time by 30.7% and 66% for waiting in the waiting room and waiting in the exam room before treatment, respectively. Lastly, the practice will see an increase in their patient capacity per week by 46%. As a result of the improvement scenarios it is evident that the practice can handle an increase in their physician clinical capacity as well as an increase in patient volume without having a negative impact on patient waiting time.

The use of simulation and the partnership between system engineers and key stakeholders throughout the study allowed stakeholders to change their perception of where the bottlenecks within the process were. Initially, they were certain the lab process was a bottleneck; however, this perception changed and they were able to see that the true bottleneck in the process was scheduling of resources. Understanding this as the bottleneck stakeholders saw the value in modifying resource scheduling as well as coming to the consensus that physician schedules should be shared with staff in advance. Furthermore, stakeholders came to the realization that the practice already had sufficient resources and it was eye opening for them to see how underutilized their MOAs were. Additional recommendations made to improve MOA utilization were; to establish a true MOA pool and no longer have MOAs assigned to individual physicians as well as move additional administrative tasks from physicians to MOAs.

Involving key stakeholders throughout the modeling process helped to mitigate resistance and obtain buy-in. Initially, the process flow was explained through policies and procedures by managerial staff but during the process flow validation frontline staff involvement revealed that the day to day operations does not necessarily mirror the policy and procedures. This helped us to model an accurate reflection of the practice. Obtaining this buy-in allowed simulation to be used as a real problem-solving tool to provide healthcare decision-makers in an outpatient endocrinology practice with the knowledge and insight to make appropriate decisions for improvement.

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