Time Saves Lives: Optimizing Pediatric Clinic Patient Visit Times

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***Abstract*—Inefficient workflows in hospitals are a growing problem as the demand for medical services increases faster than an institution's ability to assist patient needs. To support the population's medical demand, hospitals must optimize their current patient visit cycles to lower cycle times with the aim of increasing throughput. This study focuses on identifying inefficiencies of the patient visit cycle at the Orthopedic Clinic of Children's National Hospital in Washington, DC. The project goal compromises three main research questions: (i) How can the patient visit cycle be modeled to demonstrate interdependencies between the cycle segments and segment actions? (ii) How can the cycle segment times be represented as mathematical probability distributions? and (iii) How can simulation of the patient visit cycle assess time effects of new policies? To investigate the questions, the team conducted interviews, performed observational site visits, collected data, fit data to distributions, and used the distributions to develop a simulation model in Simio™ of the patient visit cycle. The team will apply policies to the simulation to assess the effects on the patient time in system and total throughput. From this analysis, suggestions can be made to the clinic. The proposed improvements include adjustments to labor schedules, patient arrivals, and provider rooms that optimize the workflow of the Orthopedic Clinic at the Children's National Hospital.**

Keywords—Discrete Systems Simulation, Hospital Process Optimization

I. INTRODUCTION

A. Problem Statement

Healthcare systems are fundamental in any society to provide access to medical services for improved health, wellbeing, and quality of life. Therefore, it is crucial these systems or healthcare systems function efficiently. The current demand for health care services is typically much greater than the capacity to manage patients [1]. Lack of access to hospitals and medical services creates challenges for patient wellbeing and the success of hospitals. The Orthopedic Clinic at the Children's National Hospital (CNH) is committed to meeting patient demand, and their Community Benefit program specifies that their mission is to improve healthcare access for surrounding communities [2]. Identifying areas that are functioning inefficiently in the current system will allow for process improvements that lower the time a patient is at the clinic. This would encourage higher patient throughput and increased customer satisfaction to support the goals of the hospital.

B. Background

Long patient-wait times harm the patient experience and worsen overall system productivity to help more patients. Studies have shown that hospitals across the country struggle with capacity management leading to long wait times, negatively impacting patient satisfaction with the hospital [3]. However, sources of inefficiencies vary between hospitals and departments due to differing patient visit cycles. Consequently, it is difficult for hospital operations to identify which inefficiencies have the greatest detriment to their own system.

Fortunately, strategies for increasing hospitals' capacity management are a growing area of research. There have been numerous studies analyzing the implementation of different policies to lower patient visit cycle times. An investigation by Cincinnati Children's Hospital found that employing a capacity management dashboard highlighted the bottlenecks and inefficiencies in their hospital. The dashboard helped nurses recognize when capacity was being reached and execute contingency plans to help patients and procure resources [4]. With the employment of the dashboard, the hospital was able to address their capacity management inefficiencies and lower patient visit cycle times.

Consistent with Cincinnati Children's Hospital, U.S. pediatric hospitals at large operate at or near capacity, including the Children's National Hospital (CNH) in Washington, DC. Ranked the fifth best pediatric hospital in the nation and the first in newborn care according to U.S. News and World Report, CNH is the only exclusive provider of pediatric care in the DC metro area [5]. The CNH main hospital houses 323 beds, facilitating more than 17,000 surgeries, 669,000 outpatient visits, and operations in 60 different specialties every year. Like other departments, CNH's Orthopedic Clinic is currently close to patient capacity and suffers from long wait times. Solutions to these inefficiencies require a system analysis to optimize the patient visit cycle.

C. Purpose

The purpose of this project is to identify areas of inefficiency in the CNH Orthopedic Clinic and suggest policy changes that help to lower the time a patient is in the system. The system analysis will highlight cycle segments with long processing times, extensive queues (i.e., long wait times), and/or high utilization. By pinpointing inefficient areas and actions, the team can suggest policies to diagnose the issue. In addition, simulating the policy changes in the clinic will

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help to assess the magnitude to which the patient visit cycle time can be lowered. With these cycle time improvements, the clinic can work to increase the throughput of patients and target their immediate capacity management issue. This system analysis provides recommendations for policy implementations that achieve these goals with the ability to better pediatric patient care.

D. *Significance*

The mission of CNH is to be "champions for children." Specifically, their goal is "to not simply cure illness, but to care for each child's entire well-being" [2]. To achieve this aim of ensuring patient wellness, it is critical to ensure efficiency in the patient visit. Any inefficiencies in the patient visit cycle cause long wait times and lower throughput. Long patient-wait times can be detrimental for the patients and families of the hospital and limit access healthcare. This is especially detrimental for the CNH community as children are a vulnerable population. In response to the pediatric hospital capacity management problem in 2022, CNH put out a statement saying "when a child in our hospital or emergency department is facing a life-threatening emergency, there is no wait time" [6]. However, *NBC Washington* wrote about the severity of this issue, reporting that the hospital was "near capacity and is expected to stay that way" [7]. An analysis on the patient visit cycle through simulation can allow hospitals to identify inefficiencies in their operations that could be addressed to lower cycle times.

E. *Scope and Limitations*

The scope of this study is limited to lowering patient cycle time through labor improvements, schedule changes, and adjustments to room allocation. The cost of implementing these changes is not considered. Due to time constraints, the team limited collecting data to one clinic site on Mondays, Tuesdays, and Fridays—days with similar patient visit cycles. Additionally, the collection and use of empirical data resulted in limitations in goodness of fit statistical testing. Assumptions are made based on expert judgment when selecting probability distributions of best fit. The simulation cannot directly replicate the Orthopedic Clinic therefore some assumptions will be needed. However, despite these assumptions, discussion with hospital personnel provides verification that the simulated visit cycle and identified inefficiencies are reflective of the current clinic.

II. PROJECT GOALS AND RESEARCH QUESTIONS

The project goal was to model a current patient visit cycle at the CNH Orthopedic Clinic to identify inefficiencies and assess the effects policies would have on lowering cycle time. The goal was decomposed into three main research questions:

RQ1. How can the clinic patient visit cycle be modeled to demonstrate the interdependencies between the cycle segments and segment actions?
RQ2. How can the visit cycle segment times be represented as mathematical probability distributions?
RQ3. How can simulation of the patient visit cycle assess time effects of new policies?

To achieve this goal and complete the research questions, the team followed three main phases:

A. *Model the clinic patient visit cycle*

A qualitative model was created to reflect a patient's visit at the clinic. The "patient visit cycle" was defined as the time from when a patient enters the clinic until the patient checks-out. The patient visit cycle was broken down into stages defined as "cycle segments" and further into actions within the segment defined as "segment actions." This breakdown is modeled in Fig. 1 below.

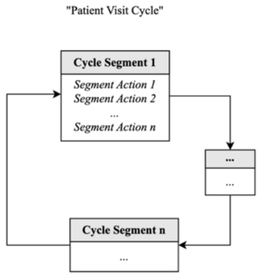

Fig. 1. Nominal Patient Visit Cycle Model.

B. *Fit data to mathematical distributions*

The model from RQ1 was used to guide the data collection and the distribution fitting. Empirical time data for each segment action of the patient visit cycle was collected through direct observation. The time data was then converted to durations and fit to mathematical probability distributions. Once tested for goodness of fit using the Chi-squared test, the obtained distributions were applied to the simulation in RQ3.

C. *Simulate the clinic patient visit cycle*

The simulation was created using the mathematical distributions, patient visit model, and work schedules obtained from the clinic. The program used, Simio™, is an object-oriented simulation software that uses servers and processes to visualize and run a queuing model [8]. This software was used to simulate the patient flow on a regular clinic day (Monday, Tuesday, and Friday).

From a working simulation, the team identified "inefficiencies" in areas with long queues and high utilization rates. The inefficiencies were addressed by implementing "policies"—operational or resource changes—that lowered cycle time.

III. METHODOLOGY

The following section breaks down the methodologies by the four main research questions.

A. *Model the clinic patient visit cycle*

Semi Structured Interviews. The team interviewed the Orthopedic Clinic experts on the operations of the clinic including the floor plan, the cycle segments, the segment actions, the decision points, the patient flow, etc. From the interview results an initial patient visit model was drafted.

Observational Site Visits. In-person walk throughs of the clinic site substantiated the initial model. The site visits also allowed for testing and prototyping of data collection methods to determine the most accurate and fruitful approach.

Refinement of Initial Model. From the observational site visit, the initial model was refined to produce the final patient visit cycle model for use in the data collection and simulation. The final model can be seen in Fig. 2.

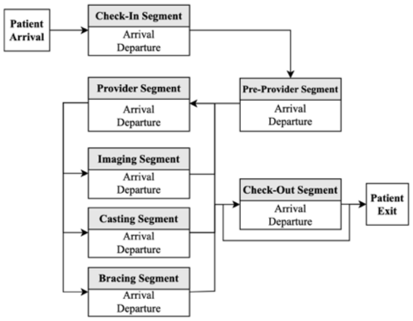

Fig. 2. Final Patient Visit Cycle Model.

B. Fit data to mathematical distributions

Observational Data Collection. A Google Sheet was used by the team to record patient time data as the individual moved through the cycle segments. The team was stationed in different areas of the hospital and tracked the "arrival" and "departure" time of each segment action in addition to the patient's arrival and departure of the clinic. Patients were traced through the cycle through descriptions of their physical attributes and clothing attire to maintain HIPAA compliance.

Data collection was limited to Mondays, Tuesdays, and Fridays which were defined by the staff as "regular clinic days." Data collection was conducted over the course of three months until a large enough sample size was obtained given the time constraint ($n \geq 70$ for each cycle segment excluding "Bracing", "Casting", and "Check-out" where $n \geq 15$ sufficed). The empirical time data was then converted to duration data and summary statistics of the findings can be seen in Table I below.

TABLE I. SUMMARY STATISTICS [MIN] OF CYCLE SEGMENT

Cycle Segment	n	Min	Max	Avg	Med
Interarrival Times	127	0.00	23.00	5.29	4.00
Check-In Duration	153	0.00	3.00	0.91	1.00
Pre-Provider Duration	135	0.00	14.00	1.58	1.00
Provider Duration	98	1.00	29.00	7.21	6.00
Imaging Duration	72	1.00	52.00	8.22	5.00
Casting Duration	15	4.00	73.00	29.13	22.00
Bracing Duration	19	4.00	56.00	23.79	23.00
Check-Out Duration	32	0.00	9.00	2.34	1.00

Fit Data to Distribution. The team used @Risk 8.0 Palisade© Software, a software add-on in Microsoft® Excel, to fit the empirical duration to different distributions. For the best results, a lower limit and upper limit were selected with a fixed bound of zero and an open bound extending to infinity, respectively. Additionally, since the data was obtained from an unknown distribution, a parametric bootstrap was run with 1000 resamples and a confidence level of 95%. Likewise, the goal of ranking distributions based on similarity suggested the Chi-squared binning arrangement was based on equal probabilities. Each of the cycle segments were fit to distributions using @Risk 8.0. Examples of cycle segment histograms and their fitted distributions are shown in Fig. 3 below.

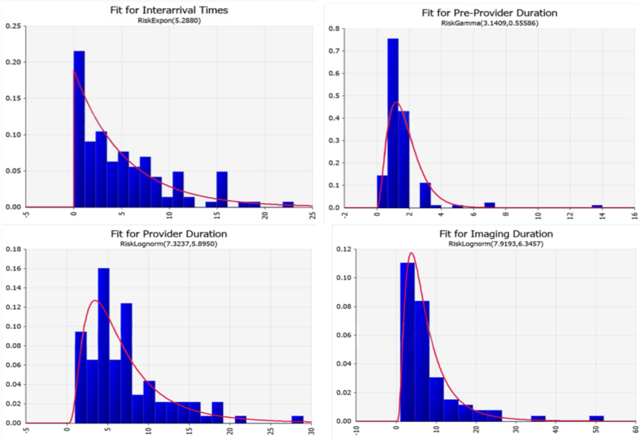

Fig. 3. Sample Distributions from @Risk Fit

Goodness of Fit Testing. The main test statistic used in determining the best fit was a Chi-squared considering it tests whether a sample of data (discrete or continuous) came from a population of a certain distribution. The hypotheses for this test are given in equations (1) and (2) [9].

$$H_0\text{: The data follow a specified distribution.} \tag{1}$$

$$H_a\text{: The data do not follow the specified distribution.} \tag{2}$$

For the purposes of the team's study a significance level of 10% was used ($\alpha=0.100$) suggesting that the distribution with the highest Chi-squared p-value (for $p>0.100$) was the best choice distribution. A table of the final distribution selections can be found below in Table II followed by a justification for the choices made.

TABLE II. FITTED PROBABILITY DISTRIBUTIONS BY CYCLE SEGMENT

Cycle Segment	@Risk Fit	PDF	Parameters	Chi-Sq Statistic	p-value
Interarrival Times	Exponential	$\lambda e^{-\lambda x}$	$\lambda = 6.2302$	26.820	0.001
Check-In Duration	Exponential	$\lambda e^{-\lambda x}$	$\lambda = 0.90850$	1427.353	0.000
Pre-Provider Duration	Gamma	$\frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$	$\alpha = 3.1409$ $\beta = 0.5559$	485.051	0.000
Provider Duration	Lognormal	$\frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(lnx-\mu)^2}{2\sigma^2}}$	$\mu = 7.3237$ $\sigma = 5.8950$	20.306	0.013
Imaging Duration	Log-Logistic	$\frac{(\beta/\alpha)(x/\alpha)^{\beta-1}}{(1+(x/\alpha)^{\beta})^2}$	$\beta = 5.8468$ $\alpha = 2.5548$	30.500	0.001
Casting Duration	Exponential	$\lambda e^{-\lambda x}$	$\lambda = 29.133$	0.400	0.789
Bracing Duration	Exponential	$\lambda e^{-\lambda x}$	$\lambda = 23.789$	1.421	0.589
Check-Out Duration	Exponential	$\lambda e^{-\lambda x}$	$\lambda = 2.3438$	20.875	0.000

As previously mentioned, any cycle segment with a Chi-squared p-value greater than 0.100 is considered to have come from the population of the fitted distribution. However, as seen in Table II, due to the limitations of self-collecting data many cycle segments had small p-values. For the purposes of this study, a distribution was still selected based on the fit with the highest average ranking of all fit statistic tests performed in @Risk 8.0 (i.e., Akaike, Bayesian, Average Log-Likelihood, Chi-Squared Statistic, Kolmogorov-Smirnov Statistic, Anderson-Darling Statistic). Recognizing the distributions

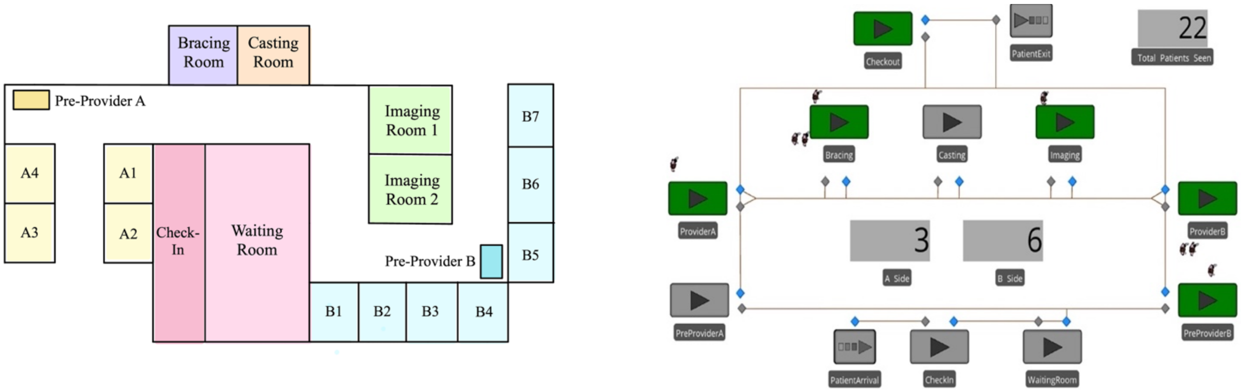

Fig. 4. Comparison of Orthopedic Clinic Floor Plan (left) and Final Simio^{TM} Simulation (right)

with low p-values were still important to understand where there could be room for error.

C. Simulate the clinic patient visit cycle

Create Simulation. To create the simulation, the team used Simio™, a simulation software that constructs a virtual model of an operation allowing for a system analysis to be performed [8]. Each of the cycle segments defined in the final patient visit cycle model (Fig. 4) are represented by “servers” in the simulation. A “source node” and “sink node” were added to simulate the patient arrivals and departures, respectively. The floor plan of the clinic (Fig. 4) helped define the simulation’s physical layout. The fitted distributions found in @Risk 8.0 were then added to each of the cycle segment servers to reproduce the service times of processes in the Orthopedics clinic (Fig. 4). Further details were incorporated to best reproduce clinic operations including arrival rate tables, work tables, path weights, and room capacities. The decisions made were the following:

A time-varying arrival table was used based on the hours of operation of the clinic and the obtained interarrival time distribution found in Table II. The team simulated patients arriving at the clinic from 8:00am-11:30am (morning shift) and 12:30pm-4:00pm (afternoon shift). A 30-minute buffer period with no patient arrivals occurred at the end of each shift in addition to a 30-minute lunch break from 12:00pm-12:30pm. The team assumed the patient interarrival rate to follow an exponential distribution with λ=5.29 suggesting patients arrived every 5.29 minutes, or equivalently 11.35 arrivals each hour. This was applied to the table and set as the pattern for arrivals.

Similarly, a work table was added to all servers dictating that the processes should only be running from 8:00am-4:30pm with a 30-minute break for lunch. Additionally, for processes that had multiple personnel (e.g., “Check-In”, “Imaging”, and “Provider B”) capacities were added to reflect the accurate number of people working on the process.

To represent patient flow through the system most accurately, path weights were added between each of the servers based on observational data calculations. For example, the team calculated the percentage of patients who went to the A-side providers vs. B-side providers, 28% and 72% respectively. Those numbers were added to the paths from “Waiting Room” to the two pre-provider sides. This same process was done for each of the paths including the return path from the “Bracing”, “Casting”, and “Imaging” segments. For example, when patients leave Imaging, they have an 85% chance of returning to their doctor, a 9% chance of checking out, and a 6% chance of directly leaving the clinic.

Finally, to incorporate room capacity constraints, a room count variable was added. This ensured patients only moved from the “Waiting Room” to the “Pre-Provider” segment when there was a room available for them. The A-side had 4 provider rooms and the B-side had 7 provider rooms—reflecting the actual clinic floor plan. By adding a room capacity constraint, queues formed in the waiting room, showing that wait times were impacted by a lack of available space.

Simulate Policies. The simulation was run for a sufficiently long enough duration (20 weeks) to reach a steady state. This ensured that the simulation was properly functioning and exposed long queues. The base simulation was run for one business day with 10,000 replications using an Intel® Core™ i7-7700 Quad Core Processor. Resulting in a run time of 56.2 minutes. Similarly, each policy was run for one business day, this time with 1,000 replications resulting in an average run time of 5.4 minutes. Specifically, a backlog in the “Waiting Room” server was found indicating the subsequent cycle segment processes were inefficient. Although not apparent in an 8:00am-4:30pm runtime, extending the runtime revealed a backlog which indicated the patient arrival rate (λ) was greater than the processing time (μ), making this an unbalanced system.

From this data, the team choose to analyze the utilization rates ($\rho = \lambda/\mu$) of each cycle segment server to confirm that no one process was overutilized seen in Table III. For the purposes of the study, the team looked at cycle segments with utilization rates above 75% ($\rho > 0.75$).

TABLE III. UTILIZATION BY CYCLE SEGMENT

Cycle-Segment	Utilization (ρ)	Cycle-Segment	Utilization (ρ)
Check-In	4.07%	***Provider B***	25.55%
Pre-Provider A	8.47%	***Imaging***	17.04%
Provider A	22.16%	***Bracing***	60.54%
Pre-Provider B	18.84%	***Casting***	74.60%

The only cycle segment that neared that threshold was "Casting," highlighted in yellow in the table. Therefore, a policy that lowered the utilization rate was worthy of consideration.

However, most processes had low utilization rates suggesting the issues stemmed from patient room capacity constraints instead of inefficient processes. Moreover, the utilization rates of the A-side and B-side were 74.9% and 95.6% indicating that adding provider rooms could be a policy consideration. Additionally, to lower the patient-wait times, the arrival rate could be adjusted to reduce patient overlap.

Using this information, the team independently implemented three policies into the simulation that achieved the original project goal of lowering cycle time ("time in system"):

Policy 1: Adding Another Cast Technician. This policy increased the casting capacity from one to two simulating the effects of an additional another cast technician.

Policy 2: Re-Designing Patient Arrival Schedule. This policy altered arrival rates, testing the effects of 6-18 patient arrivals per hour compared to the original 11.3464.

Policy 3: Increasing the number of Provider Rooms. This policy increased the patient capacity of A and B sides simulating the effects of adding more provider rooms to the clinic.

Root Cause Analysis. While conducting in-person site visits, the team also performed observational analyses and surveyed clinic personnel to identify inefficiencies. The following questions were asked: (1) Where in the cycle do you notice the longest wait times? (2) Where in the cycle do you notice roadblocks? (3) Do you have any suggestions as to what inefficiencies can be targeted to reduce patient-wait times? The findings and feedback corroborated the inefficiencies detected through simulation adding face validity to the orthopedic clinic simulation.

IV. RESULTS

A. Discussion of Findings

The team's simulation identified inefficiencies in the current patient visit cycle and demonstrated the effects policies would have on patient time in system and additionally the total number of patients seen. After identifying inefficient areas of the patient visit cycle the team simulated the policies. The results were as followed:

Policy 1: Adding Another Cast Technician. When implemented, the additional cast technician resulted in a lower utilization and an average decrease of 10.5% in a patient's total time in the system as seen in Table IV.

TABLE IV. SYSTEM CHANGES WITH ADDITIONAL CAST TECHNICIAN

Policy	**Casting Utilization (ρ)**	**Time in System (min)**	**Total Patients Seen**
Current State	74.6	49.2	68
Additional Cast Tech	46.8	44.0	74
Policy Effect	**-37.3%**	**-10.5%**	**8.8%**

Additionally, there is an 8.8% increase in the total number of patients seen, suggesting that adding another cast technician not only lowers the time patients are in the system, but also allows for a greater throughput.

Policy 2: Re-Designing Patient Arrival Schedule. When varying the arrival rates, the team observed that decreasing the number of arrivals per hour decreased the time in system and increasing the number of arrivals per hour increased the time in system (Fig. 5).

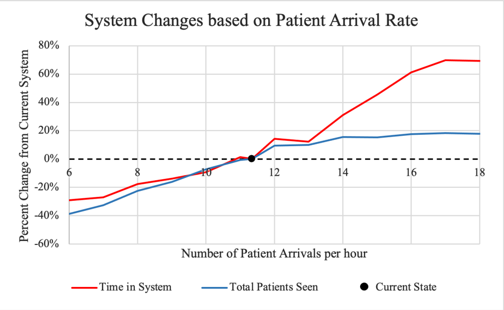

Fig. 5. Effect of Patient Arrival Rate on Time in System and Total Patients

In contrast to Policy 1, lowering the average patient time in system (red line) decreases the number of patients seen (blue line) in this policy suggestion. An ideal arrival rate adjustment is when the red line is below the blue line (under the dashed line). In other words, the arrival rate when the greatest decrease in time is less than the greatest decrease in throughput. This suggests that altering the current patient schedule to see fewer patients an hour could result in decreasing the total time in system possibly at the cost of seeing fewer patients.

Policy 3: Increasing the number of Provider Rooms. When increasing the number of provider rooms of A, B, and both A & B in the simulation (see floor plan in Fig. 4), the average time in system decreased (Fig. 6). Moreover, the greatest decrease occurs with the addition of four rooms.

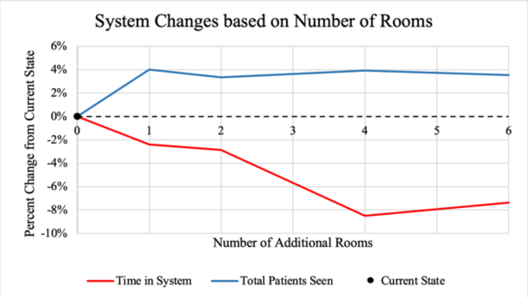

Fig. 6. Effect of Additional Rooms on Time in System and Total Patients

The team tested adding the four additional rooms to the A-side, to the B-side, and to combinations of both. Each combination and their effects on the time in system and total number of patients are seen in Table V.

When looking at different combinations of adding four rooms, testing indicated that distributing the rooms equally lowered the time in system the most—by 13.9%—as highlighted in yellow in the table. It is also noted that with an equal distribution, the patient throughput increased by 5.3%.

TABLE V. SYSTEM CHANGES WITH TWO ADDITIONAL ROOMS

Room Combination		% Change of Time in System	% Change of Total Patients
A	**B**		
Current State		0.0%	0.0%
4	**0**	-0.9%	3.4%
3	**1**	-1.5%	3.2%
2	**2**	-13.9%	5.3%
1	**3**	-9.7%	4.9%
0	**4**	-10.7%	3.0%

To further demonstrate the effects of the additional provider rooms, Table VI displays the percent of the time the A-side and B-side rooms are at max capacity. This represents the times when the clinic cannot accept more patients because the system is full. The policy lowered the percent of time at max capacity by 35.2% on the A-Side and 59.5% on the B-Side.

TABLE VI. MAX ROOM CAPACITY BEFORE AND AFTER POLICY

Side	% of Time at Max Capacity	
	Before Policy	*After Policy*
A	21.7%	14.1%
B	46.0%	18.6%

B. Anticipated Benefits

Identifying inefficiencies in the Orthopedic Clinic is beneficial to improve operations in the Children's National Hospital. The Simio™ simulation provides the hospital insight on how different policies can improve the current system, such as adding a cast technician, re-designing the patient arrival schedule, and increasing the number of provider rooms. These improvements include lowering the utilization of a process (cycle segment), lowering a patient's total time in the system (cycle time), and increasing the total number of patients seen (throughput). Although all policies achieve the main goal of lowering cycle time, the magnitude, requirements, and side effects vary per policy. A simulation analysis outlines each of these aspects, assisting the hospital in making decisions to optimize their operations. Additionally, other CNH departments with similar patient visit cycles and similar inefficiencies could benefit from this project's methodology and suggested policies.

C. Opportunities for Future Work

Future research could lead to the scalability of this project to other clinics and various industries that have customer cycles such as pharmacies, banks, or the Department of Motor Vehicles. Any industry that desires to improve the time of customers moving through a system could benefit from a system analysis using the framework of the project's methodology. Additionally, with more time and resources, the team could have extended the study to look more in depth at the visit cycles for specific days of the week or statistically compare the visit cycles across different CNH locations. Another future opportunity is simulating aberrant patient flow due to demand surge associated with high-consequence, low probability events, such in the case of disasters. Moreover, a cost-benefit analysis could be conducted to further understand the most practical policy choice. Regardless, the expectation is that future work can be conducted using this project as groundwork to improve throughput and capacity management in other areas of the CNH, other operations of the healthcare system, and even any other customer-based industry sectors.

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