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INTEGRATED SIMULATION TOOL TO ANALYZE PATIENT ACCESS TO AND FLOW DURING COLONOSCOPY APPOINTMENTS

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ABSTRACT

Colonoscopy procedures are key to reducing colorectal cancer incidence and improving outcomes. For this reason, it is important that clinics be designed to maximize access to care and to use clinic time effectively. This paper presents a simulation tool that analyzes different scheduling policies to see how they impact overall clinic operations. By simultaneously simulating both scheduling and operations, the tool can account for more variability and better predict actual outcomes. This tool can be used to inform clinics on what scheduling policies work best for their clinic and help analyze what the trade-offs will be between different policies.

1 INTRODUCTION

Colorectal cancer is the most common cause of cancer and is the second leading cause of cancer death in the US (American Cancer Society 2019). Colonoscopy procedures are one of the methods used for preliminary testing to detect this type of cancer and have been shown to reduce the mortality rate by more than 50% (American Cancer Society 2017). The trade-offs between patient access, patient and provider satisfaction, quality of care, and resource management make the scheduling of colonoscopies challenging. The aim of this project is to find the best ways to schedule colonoscopies while considering multiple criteria such as patient satisfaction, clinic utilization, appointment lead time, appointment delay, staff overtime, and clinical outcomes. We present an integrated discrete event simulation tool for scheduling colonoscopies, which evaluates the scheduling templates and policies concurrently with the operational performance of the resulting schedules to understand the above-mentioned trade-offs. By combining both scheduling and operations in the simulation, our tool enables more accurate modeling because it takes into account variability in both patient demand and clinical operations.

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2 LITERATURE REVIEW

According to Zhang et al. (2018), there are 5 main categories of simulation modeling in healthcare: Discrete event simulations (DES), agent based simulations (ABS), system dynamics (SD), hybrid modeling, and game simulations. While DES models have historically been the most popular in healthcare, other simulation models have become more popular for specific uses such as systems perspectives. For patient-centric logistics, DES is by far the most popular option (Zhang et al. 2018).

DES modeling is a form of computer-based modeling methodology (Zhang 2018). The goal of a DES model is to “comprehensively compare potential practices or strategy options” (Zhang 2018) in order to identify those that are the most efficient and effective. Simulation plays a large role in a variety of different industry operations. It wasn’t until the late 1990’s that the healthcare field took interest in using the DES tool (Zhang et al. 2018) in order to enhance their data-driven decision making. Although the healthcare industry has less experience using DES models than other industries like manufacturing, where it has been traditionally used (Babulak and Wang 2008), the simulations that have been created, such as one that reduces patient time in a glaucoma clinic (Guo et al. 2019) have shown to be effective. The healthcare industry has begun to rely on simulation in hopes of improving clinical operations, for example, in gastroenterology clinics. DES models are becoming known as a “more practical and flexible modeling technique” for complex and dynamic health care situations (Zhang 2018). Since our model is mostly patient-centric, we created it as a DES.

Much research has been done using simulations to improve operations of healthcare clinics such as Aeenparast et al. (2013), Norouzzadeh et al. (2015), Rohleder et al. (2011) and Guo et al. (2019). Most of these models analyze how changing resource allocation and patient flow can impact important metrics such as patient wait time and provider overtime. There has also been a significant amount of research done on the optimization of scheduling in healthcare clinics such as Muthuraman and Lawley (2008) and Chen et al. (2015). These models attempt to find the best scheduling policies by analyzing different scenarios and their outcomes. Specifically, in the model created by Chen et al. (2015), different scheduling policies are tested and then optimized according to an objective function while considering trade-offs between some of the metrics. While this model accounts for the variability with procedure times it does not incorporate variability for patient arrival times or no shows.

There have been multiple models created that specifically focus on gastroenterology clinics and colonoscopy procedures. For instance, Shehadeh et al. (2020) uses a mixed integer program to find an optimal appointment sequence and schedule for an outpatient colonoscopy clinic. This model places a heavy emphasis on the effect of inadequate prep on the variability of the colonoscopy procedures. Two other examples of models that focus on colonoscopies are Berg et al. (2010) and Day et al. (2014). Both models are DES which is the same method used in our simulation. The DES model from Berg et al. (2010) applies mostly to the operations of a clinic, making recommendations on the room utilization as well as suggestions on what procedure elements can be improved to make the clinic run better. This model does not have any scheduling components involved. The DES model from Day et al. (2014) on the other hand does have some scheduling components. In this model, different appointment lengths are tested in many scenarios to see the overall effect this has on important metrics such as patient wait time. However, there is no analysis done on the different policies that can be used to schedule these patients. While the model we present includes many of the methods used in these models, it has key variable components including the scheduling policy as well as the combination of operations variability that make it different from any of the models referenced.

3 SIMULATION DESIGN

The simulation models both the scheduling and operations of an outpatient endoscopy clinic. Two key assumptions that are made with the model are:

1. We are only using a single provider.
2. There are discrete sets of patient types.

The first assumption means that the simulation is only following a single provider in this simulation and other providers working at the same clinic are not taken into consideration. This simplifies the model but also limits some of the variability and accuracy. The second assumption means that the patient population is able to be separated into different groups based on characteristics, which could be things like age or family history of cancer. Figure 1 represents the overall flow and logic of our simulation. The top flowchart represents the scheduling portion of the code while the bottom flowchart represents the operations portion of the code. The model is coded in C++ in 2015 version of Visual Studio.

The determination of sample size is done via the Monte Carlo Approach, discussed later in detail in section 4.3. The parameters of the simulation are primarily determined from real-world data obtained from the gastroenterology clinics at Michigan Medicine; the daily operational time of the clinic in our simulation is based on this data, so is the patient arrival rate and procedure duration. The procedure durations are randomly drawn from truncated normal and truncated exponential distributions for simple patients and complex patients respectively. We do not validate this against the real-world performance because the focus of our model is less on replicating what happens in the real-world and more about modeling and understanding the interaction between the scheduling process and operations process of the clinics. However, we do use real-world data in the analysis as shown in section 4 to ensure accuracy. The

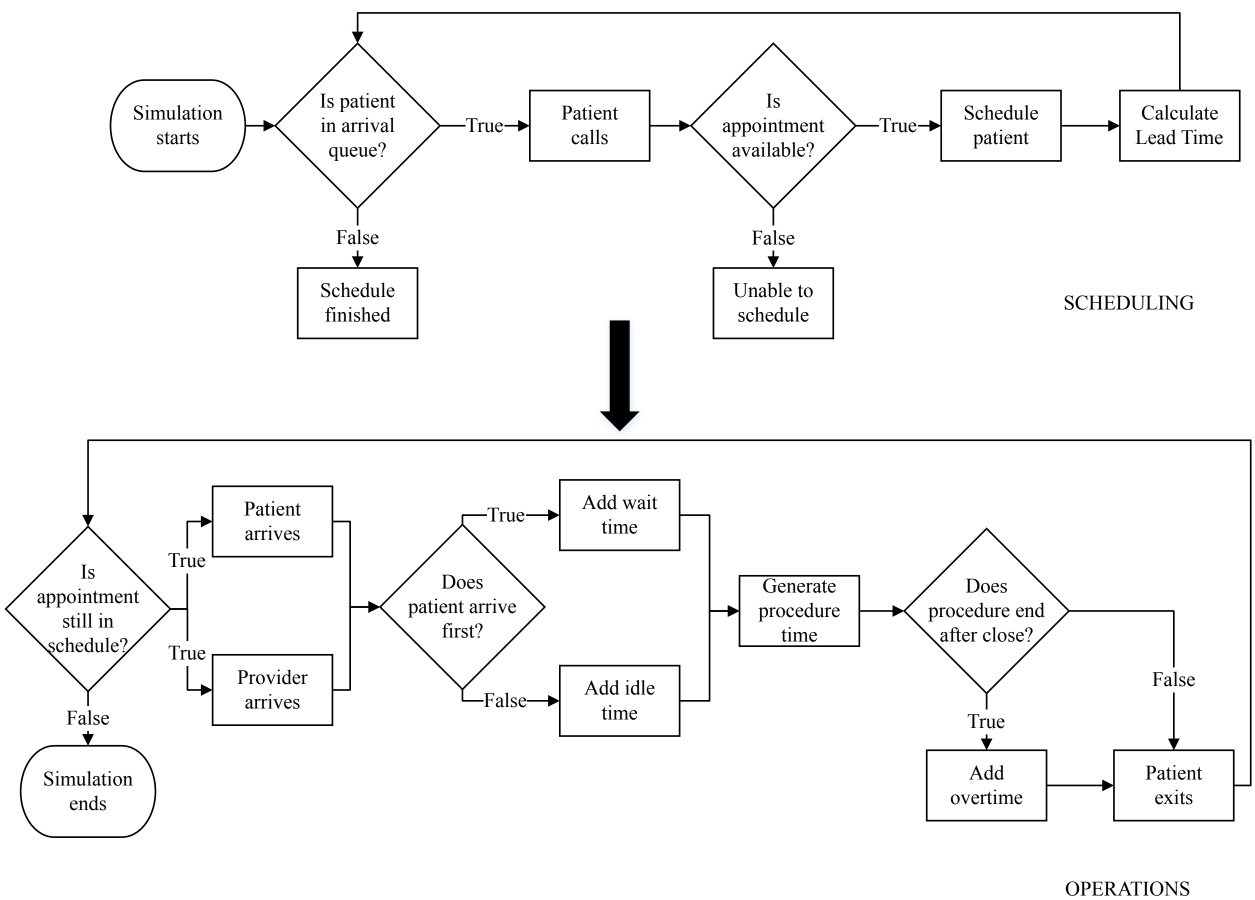

Figure 1: Simulation flow.

simulation starts by generating patient arrivals. From there the patient will be scheduled according to the given schedule policy and template input by the user. This is done for all patients generated in the time horizon. Once the simulation reaches the end of our time horizon, the completed schedule is passed on to the operations portion of the code. In the operations portion, each appointment in the schedule is looped through. For each appointment there is variability in the arrival time of the patient, as well as the time the provider becomes available. The patient can arrive early or late for the appointment, while the time when the provider becomes available depends on the end time of the previous procedure. Once the patient has arrived and the provider is available, the procedure can begin. After all the appointments are looped through, metrics are gathered on how the clinic operated throughout the simulation and the metrics are output. In the next sections, each portion will be described in further detail to explain the inputs, logic, and outputs.

3.1 Scheduling

The scheduling portion of the code starts by randomly generating a stream of patients for the given time horizon. This is done using specific input parameters for each patient type based on an average number of arrivals. When a patient calls to request an appointment, they go through the scheduling process, which is specified by the type of scheduling policy that is input. A scheduling policy is something like first come first serve, with a common variation being first come first serve by patient type, meaning patients may only be scheduled to appointments specifically made for their patient type. Scheduling policies are very flexible and can be quite simple or more complex. Scheduling policies are predefined in the program and selected by the user as an input parameter. Based on the scheduling policy, patients are assigned an appointment slot in the given schedule template. The schedule template is the set of appointment slots for each day in the given time horizon and is selected by the user as an input. This scheduling procedure is done for all patients and metrics are kept on how many patients are scheduled, how many are unable to be scheduled, the number of appointments they are offered, and the lead time for each patient (the time between when they call and when their appointment is scheduled). Once complete, a finished schedule is then passed to the operations portion of the code.

3.2 Operations

In the operations portion of the code, the completed schedule is taken in and simulated. This is done by going through each appointment chronologically in the schedule. The appointment process is simplified in the simulation to only include the arrival, procedure, and exit of the patient. While there are many stages in an appointment such as the intake, procedure, and recovery, the procedure portion is used to account for all of these. By combining these into one stage, some of the variability in and between stages is limited. To start the appointment, an arrival time is generated based on the given input parameters. Patients may arrive early or late and this can affect the start time of their procedure. Once both the patient and the provider are ready for the procedure, a random procedure time is generated using the parameters for the given patient type. For this generated duration the provider is unable to see other patients. After the generated time, the patient leaves the clinic and the provider is free to work on other patients. The procedure could take more time or less time than allotted by the appointment slot and this may affect the start time of the next procedure as well as the metrics. If the procedure does take more time than allotted, the next patient will have to wait until the provider is free which adds to the wait time. If the procedure takes less time than allotted the provider will be idle until the next patient arrives. If the last patient in a day goes over the allotted time, the provider must work overtime. This process is repeated for every appointment in the given schedule. Once all appointments have been simulated, metrics such as wait time per patient, provider overtime, and provider idle time are gathered.

4 ANALYSIS AND RESULTS

4.1 Goal of Analysis

In this section, we present some basic analyses done using the simulation tool. The goal of these results is not to give specific recommendations for how clinics should schedule their patients. Instead, we show that the combination of variability with the scheduling and operations portion of a clinic is very important to consider when trying to manage the trade-offs between metrics.

4.2 Explanation of Scenarios

In the analyses we consider three separate cases to test. For each of the cases we have a patient population that has two different types, a simple patient which has a mean appointment length of 39 minutes and a complex patient which has a mean appointment length of 62 minutes. The first case (Case 1) is a very basic type of scheduling template and policy, where the template consists of ten 45-minute appointments running from 9 am - 4 pm. Patients in this scenario are scheduled on a first come first serve basis and since all the appointments are the same, they can be scheduled to any of them. The second case (Case 2) has a different scheduling template which has four 40-minute appointments for simple patients followed by one 60-minute appointment for complex patients repeated twice for a total of ten appointments going from 9 am - 3:50 pm. An image of the schedule template for each case is shown in Figure 2.

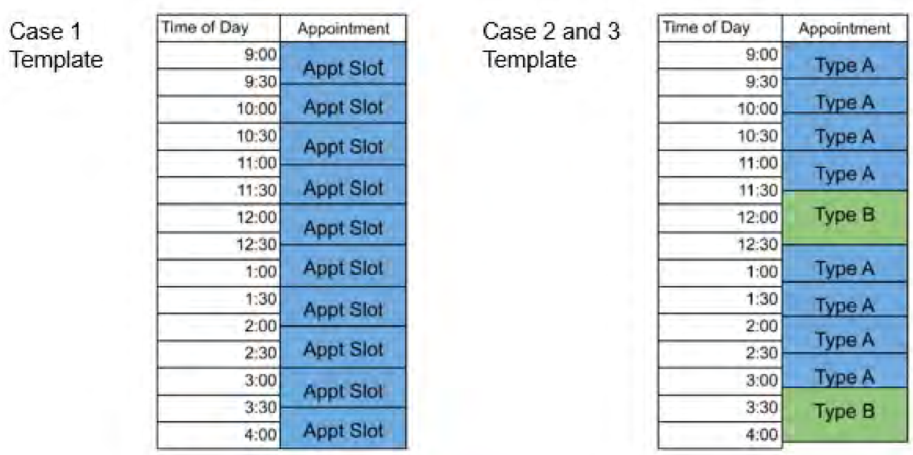

Figure 2: Schedule templates.

The scheduling policy is also different in this scenario because patients are scheduled first come first serve by type, meaning that patients can only be scheduled to appointments that fit their specific type. The final case (Case 3) we analyze is very similar to the second case except this time we add in patient preferences for the simple patients. For a simple patient there is a 25 % probability that on any given morning or afternoon for each day that they prefer not to be scheduled at that time. The complex patients do not have any preferences for the scenario. We also consider the lag time for each patient while scheduling them. The lag time is defined as the number of days elapsed from the time when a patient calls to the time when we start searching for the possible appointment slot for the patient. Table 1 shows our simulation inputs for each.

Table 1: Simulation inputs by case.

Case	Number of Replications	Time Horizon	Number of Patient Types	Lag Time	Schedule Template	Scheduling Policy
1	650	6 months	2	5 days	All-45 Minute Appointments	First Come First Serve
2	650	6 months	2	5 days	40 and 60 Minute Appointments By Type	First Come First Serve By Patient Type
3	650	6 months	2	5 days	40 and 60 Minute Appointments By Type	First Come First Serve By Patient Type with Preferences

4.3 Justification for Number of Replications Used

For determining the sample size of replication for our analyses, we use the Monte Carlo approach. Initially, we start with a small sample size $M_{assumed}$ = 10 and get the mean and standard deviation for the relevant metric (in our case we take lead time for both types of patient population case by case). We have chosen the standard error to be 0.5 days on the confidence interval of 95%. The formulation (Selecting the Sample Size - Analytica Wiki 2018) is, the sample needed to estimate the mean of A with given confidence interval smaller than the width W is given by:

$$M_{required} > \left\lceil \left(\frac{2CS}{W}\right)^2 \right\rceil \tag{1}$$

where:
$M_{assumed}$ - initial sample size of the replication,
A – chosen metric (here it is the lead time for complex patient type),
$\overline{A}$ - mean of the metric across the number of replications,
S - standard deviation of the metric A,
C – z value at chosen confidence interval (95% in our case),
W - standard error or width of confidence interval (0.5 days in our case),
$M_{required}$ – required sample size of the replication.

We use the above equation (1) to calculate the sample size of the replications required so that the results from analyses are statistically significant. Based on the calculations we find that 650 replications (rounded up to the nearest fiftieth integer multiple) for the time horizon of 6 months is adequate to get the 95% confidence interval with a width less than 0.5 days and the simulation takes on an average 40 seconds to complete. Table 2 shows the sample size of replication across different $M_{assumed}$.

Table 2: Replication calculation.

$M_{assumed}$	C	S	W	$M_{required}$(exact)	$M_{required}$(rounded up)
10	1.96	3.16684	0.5	616.43	650
100	1.96	3.16136	0.5	614.29	650
200	1.96	3.13605	0.5	604.50	650
400	1.96	3.25	0.5	649.23	650
600	1.96	3.1515	0.5	610.47	650
800	1.96	3.1035	0.5	592.03	600
1,000	1.96	3.15707	0.5	612.63	650

4.4 Results

The three cases we analyze here give distinct and revealing results. When moving from Case 1 to Case 2, average wait time across any type of patient, provider idle time, and provider overtime all see major improvements. Moving from Case 2 to Case 3 we observe the same improvements but with smaller magnitudes. While we observe the same trend moving from Case 1 to 2 to 3 for the simple patients in terms of average lead time, for the complex patients the trend was reversed, i.e., the average lead time saw increases from Case 1 to 2 to 3.

The results and comparisons across the three cases are tabulated in Table 3. Comparing Case 1 with Case 2, we see a 5.7% decrease in the lead time for simple patients in Case 2, while the lead time for complex patients is increased by 75.8%. We attribute this to the policy difference in scheduling for both cases; in Case 1 we have first come first serve basis so any patient can get any slot, hence, giving every patient equal preference. However, in Case 2 the complex patients are scheduled only twice a day, thus fewer slots are available to them and hence the higher lead time. This result is quantitatively supported by the fact that in both Case 1 and 2, we have 46,800 minutes and 41,600 minutes, respectively, allocated for simple patients. In both cases we have 1,020 and 1,019 simple patient arrivals and hence scheduling them will need 45,900 minutes and 40,760 minutes respectively. Thus, we have more time allocated to simple patients than required. While the case is opposite for complex patients, we have 283 patients in both cases with 11,700 minutes and 15,600 minutes allocated. However, scheduling 283 patients requires 12,735 minutes and 16,980 minutes respectively. Also, in Case 2, the time allotted is short by 1,380 minutes (note that Case 2 has 60 minutes for every complex patient as opposed to 45 minutes in Case 1) while case 1 is short by 1035 minutes, thereby Case 2 has a higher lead time for complex patients. But we have to note that we are tailoring for better appointment duration depending upon patient type, we see better time utilization overall such as the decrease in the average wait time for any patient we see of about 66.38% from Case 1 to Case 2. We see a similar trend in provider overtime and provider idle time with a decrease of about 79.37% and 4% respectively.

Comparing Case 2 and Case 3, which have a slight difference in terms of simple patients getting preferences in Case 3 i.e. there was a 25% probability of the offered appointment being declined. Moving from Case 2 to 3, we see about 3.15% and 0.86% increase in the average lead time for simple and complex patients respectively. This increase is due to the preferential appointment selection by simple patients. The rest of the metrics follow the same trend as in Case 1 to 2 transition, where we decrease of 0.42%, 0.22% and 0.80% in average wait time, provider idle time and provider overtime respectively. Albeit we see only a small magnitude of improvement in these metrics while using the policy of Case 2 versus Case 3, this is an indication of how the preferences of patients can play an important role in appointment scheduling. Table 3 shows the results and comparisons for all the cases in analyses.

Table 3: Results and comparisons.

Case	Lead Time for Simple Patient (Days)	Lead Time for Complex Patient (Days)	Wait Time per Patient (Min)	Provider Overtime per Day (Min)	Provider Idle Time per Day (Min)
Case 1	6.781	6.783	7.974	12.506	46.185
Case 2	6.395	11.925	2.683	2.578	44.334
Case 3	6.596	12.028	2.672	2.558	44.238
Case : 1 v 2	↓ 5.7%	↑ 75.8%	↓ 66.38%	↓ 79.37%	↓ 4%
Case : 2 v 3	↑ 3.15%	↑ 0.86%	↓ 0.42%	↓ 0.80%	↓ 0.22%

5 CONCLUSION

We develop, implement, and evaluate an integrated simulation tool for evaluating scheduling policies and their impact on patient access and operational performance. This simulation tool allows new policies to be tested robustly at low cost. From the results of the analyses, we conclude that using a first serve by-type scheduling policy helps to reduce the overall patient wait time greatly but tends to increase the lead time for less frequent patients (or in our case complex patients). We also see how the template of the schedule plays an important role while using a by-type scheduling policy. This is evident from the results of Case 1 and Case 2, where the scheduling of complex patients changes from being every fourth slot to just two slots in the whole day. We conclude that the pros and cons of any particular scheduling policy are based on the trade-offs that we are willing to make. For example, if we want lower lead time for complex patients, then we should prefer the simple first come first serve policy, but this will be at the expense of higher wait time for patients in general. So, the trade-offs are part and parcel of any scheduling policy that is used. If there is improvement in provider satisfaction, patient convenience, and clinical utilization, then it may be at the expense of clinic overtime, decreased access to patients, and decreased patient satisfaction.

We are able to test basic policies against some new policies and analyze how the trade-offs are reflected in the selection of the different policies. This simulation tool is generalized to the level that other clinics can modify it to model their own operations and test their existing and new proposed policies.

For future work, we would like to enhance our model to account for more variability and better represent actual clinic operations. To do this we will start by adding multiple providers, which will allow the simulation to account for the variability in the scheduling as well as operations of the clinic that is not accounted for by using a single provider model. In addition, we could expand our appointment operations to include multiple stages (e.g., intake, procedure, recovery) instead of just one, which will allow for more variability and increase the accuracy of the model.

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