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USING DISCRETE-EVENT SIMULATION TO FIND WAYS TO REDUCE PATIENT WAIT TIME IN A GLAUCOMA CLINIC

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ABSTRACT

Long wait times is one of the most common complaints from patients visiting the glaucoma clinic at the Kellogg Eye Center at the University of Michigan (UM). Long wait times have also been reported as a barrier to glaucoma care in other clinics as well. To address this issue, we develop a discrete-event simulation model to identify bottlenecks in the clinic that cause the majority of patient wait time. Different policies in terms of resource supplementation, i.e. adding staff and the corresponding equipment and exam rooms, are then accordingly proposed. We evaluate each of them using our simulation model through a series of what-if experiments. The most beneficial policy, considering the trade-off between patient wait time and resource supplementation expense, is proposed to the clinic to carry out in practice.

1 INTRODUCTION

Glaucoma is the second leading cause of irreversible blindness world-wide (Quigley and Broman 2006). It is a chronic degeneration of the optic nerve, the connection between the eye and the brain. The degeneration is asymptomatic until the final stages of the disease when people begin to notice blindspots and blurred vision. Once people notice symptoms, the disease is much harder to control. Therefore, in order to prevent blindness from glaucoma, people have to be diligent in coming to their ophthalmologist's appointments and taking their medications before they ever develop symptoms. Those with mild glaucoma generally visit their ophthalmologist twice yearly, those with severe glaucoma that is stable visit quarterly and those with unstable disease may have monthly or weekly appointments until the disease has stabilized (Prum et al. 2016). Patients have expressed dissatisfaction with wait times and report long wait times as a barrier to coming to clinic for care (Leiba et al. 2002; Lee et al. 2013). The Institute of Medicine's (IOM) report on health care quality, Crossing the Quality Chasm, states that providing timely, efficient, and patient-centered care are critical for improving the quality of medical care in the United States (Barger 2003). Thus, we instituted a passive continuous time-motion study system using radio-frequency identification (RFID) technology in our glaucoma clinic at the University of Michigan to capture patient wait times at a granular level and inform discrete-event simulation (DES) modeling of clinic flow.

DES can play an important role in improving the quality of service delivery in healthcare systems (Jun et al. 1999; Günal and Pidd 2010). Particularly, this technique has been widely applied to model the patient flow in outpatient clinics to find ways to reduce patients' wait time and/or length-of-stay during their visits (Duguay and Chetouane 2007; Rohleder et al. 2011; Pan et al. 2015). With its flexibility, efficiency and low-cost features, decision makers can use DES to construct and improve patient appointment schedules as it can take various uncertainties into consideration simultaneously (Harper and Gamlin 2003; Guo et al.

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2004; Cayirli et al. 2006; Liang et al. 2015). In addition, policies including resource allocation and supplementation can be efficiently evaluated before they are actually carried out (Norouzzadeh et al. 2015; Yip et al. 2016; Babashov et al. 2017; Berg et al. 2018). As all resources in a clinical environment are scarce and changing policies can be extremely expensive, DES can help decision makers to better manage risks in their actual clinic operations.

In this study, we use DES to identify potential ways to inform policy changes that would reduce patient wait times in the University of Michigan glaucoma clinic. Through a visualization of the resource waiting queue, we identify where bottlenecks to patient flow exist in the clinic and where the majority of patient wait time occurs. A resource supplementation strategy in terms of adding staff is then proposed, tested and evaluated. This simulation model allows us to compare different policies and justify the most appropriate one for the decision maker to implement in reality considering the trade-off between the amount of wait time reduced and the cost of the extra resources required.

The rest of this paper is organized as follows: in Section 2, we provide a detailed description of the problem that we are considering; in Section 3, we describe the DES development and the model inputs; in Section 4, we present our computational experiments; and in Section 5, we describe our conclusions.

2 PROBLEM STATEMENT

2.1 Patient Types and Patient Flows

Patients coming to the Glaucoma clinic at UM are classified into two types: new visit patients (NP) and return visit patients. Return visit patients are further divided into 5 groups: regular (RV), visual field (VF), post-operative (PO), laser (LA) and urgent (UR). Typically, patients coming to the clinic in type NP, RV, VF and PO will first check-in at the front desk, and then wait in the main lobby to be called back into an examination room for a preliminary examination with the ophthalmic technician. The ophthalmic technician takes the first set of measurements to prepare the patient to be seen by the physician. Depending on what the physician ordered at the last examination, some patients will have a visual field test to measure peripheral vision next while others might have their eyes dilated so that the physician can examine the back of the eye, and they might go to photography for ocular imaging. Some patients in these 4 types may need to undergo all three of these steps in succession while others may need only one of these additional steps. Once the patient has dilation drops instilled, they need to wait 25 minutes before their pupils are large enough for the physician to complete the examination. If there is one resident or one fellow available at that point, patients will be examined first by one of these trainees before being examined by their attending physician. Lastly, they go to check-out where they pay for their visit and schedule their next visit before leaving the clinic. Figure 1 displays the complete flow of the patient clinic visit for types NP, RV, VF and PO, but again note that not all patients will go through all steps during their visits.

For the UR patients, the only difference compared with the regular flow (Figure 1) is that some of them will not have the attending exam performed by the attending physician.

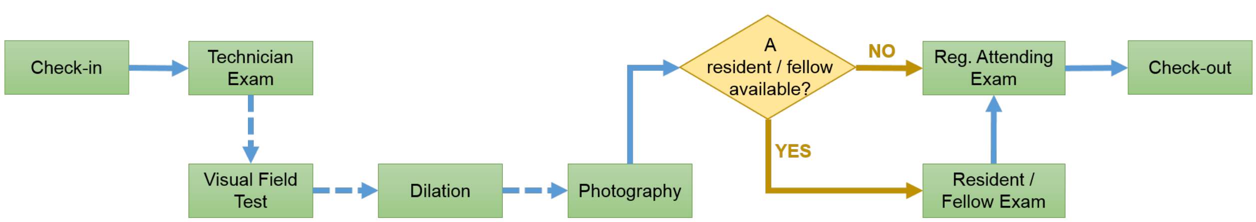

Figure 1: The complete patient flow for types NP, RV, VF and PO. The dash arrow means patients may skip the following step while the solid line points to a mandatory step that patients must go through.

However, things are quite different for laser (LA) patients. At the end of the technician exam, the technicians will either dilate the LA patients' eyes or instill other medication that needs to sit for 25 minutes.

LA patients do not require any testing, so they will not go to visual field or to photography, and they do not need an examination by a resident or fellow. Rather than a regular attending exam, LA patients will have a laser procedure performed by their attending physician in a special-equipped laser room. After that, LA patients wait for about one hour to have their intraocular pressure checked after the procedure and only if it is within the normal range are they discharged to check-out and go home. If the pressure is high, the attending physician is contacted for further management. A diagram illustrating the flow of LA patients is given in Figure 2.

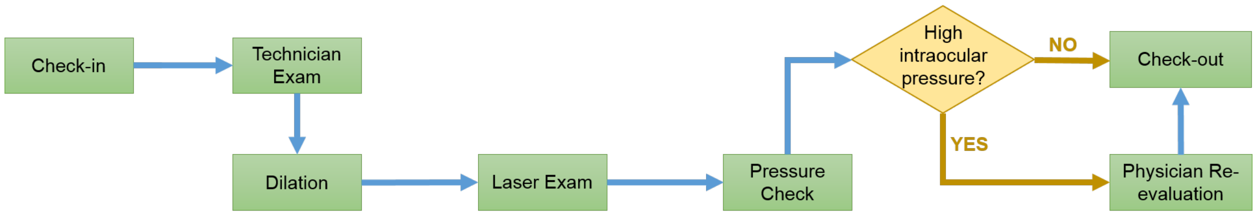

Figure 2: The flow of laser type (LA) patients.

2.2 Clinic Resources and the Appointment Scheduling Template

The glaucoma clinic has certain assigned unique resources and certain resources that are shared with the other specialty clinics at the Kellogg Eye Center (e.g. retina and uveitis, retinal dystrophies, oculo-plastics, ocular oncology, neuro-ophthalmology, pediatrics and strabismus and comprehensive ophthalmology clinics). In the glaucoma clinic, there are 5 ophthalmic technicians to do the initial work-up and 3 medical assistants to do the visual field testing. Technicians also check eye pressure for laser patients' after their procedure. The number of residents and fellows present varies day by day, but typically, one resident or one fellow is assumed to be on duty in the clinic (Section 4.2 provides a sensitivity analysis on this). Three different attending physicians are present each half-day, and each patient is assigned to their own attending physician. Laser procedures require that the laser room is available at the same time that the patient's attending physician is available, and cannot start until both are available simultaneously. Shared resources for the glaucoma clinic include the clerks at the check-in and check-out and the ophthalmic photographers. There are 2 clerks for check-in at the front desk and the 4 clerks for check-out, and they take care of patients visiting either the retina and uveitis clinic or the glaucoma clinic. There are 4 ophthalmic photographers who provide ophthalmic imaging for patients seen in all of the 8 clinics in the Kellogg Eye Center.

All resources can work in parallel, and are allocated based on the first-come-first-serve (FCFS) policy except the technicians, the physicians and the laser room. Since pressure check for laser patients takes a much shorter time, it has a higher priority than the regular technician exam in terms of requesting a technician. On the other hand, LA patients can start their laser test only when both of their attending physician and the laser room are available at the same time. Neither of these two resources can be allocated to a LA patient while the other one is still occupied by some other patient. For example, assume a laser (LA) patient and a visual field (VF) patient are both waiting to see their (same) physician, and the LA patient is available for the physician first. If the only laser room is already in use when the physician becomes available, then the VF patient will be seen by the physician first, with the LA patient waiting until both of the two resources become available. In other words, the FCFS policy for the physicians and the laser room is applied only to patients who are currently ready for that portion of the exam. Table 1 provides a summary of all resources used for glaucoma clinic operations.

Patients visiting the glaucoma clinic are scheduled according to a template, where the first appointment slot is at 7:30 am and the last is at 3:30 pm. Each 15-minute interval slot in the template is specified by the appointment time, attending physician name and the patient type, and will be assigned to a matched patient. Typically, there will be 3 or 4 available appointments for each 15-minute interval, breaking down to 1-2 patients per physician every 15 minutes.

Table 1: A list of the available number of each resource, as well as the (unit of) resource(s) required for each step. Note that again, the 3 units of the physician resource are not identical, since each patient is assigned to their own attending physician for their regular attending/laser exam.

Resource & Available Number	
Check-in Clerk	2
Technician	5
Medical Assistant	3
Photographer	4
Resident	Variable
Fellow	Variable
Physician	3
Laser Room	1
Check-out Clerk	4

Step	**Required Resource (Unit)**
Check-in	Check-in Clerk (1)
Technician Exam	Technician (1)
Visual Field Test	Medical Assistant (1)
Photography	Photographer (1)
Resident/Fellow Exam	Resident (1) *or* Fellow (1)
Reg. Attending Exam	Physician (1)
Laser Exam	Physician (1) *and* Laser Room (1)
Pressure Check	Technician (1)
Check-out	Check-out Clerk (1)

3 SIMULATION MODEL

3.1 Model Input and Assumptions

The template we use here contains in total 80 slots (patients). A brief summary of this template is provided in Table 2. Though the patients actually coming to the clinic is on average 25% fewer than the total slots, we simulate patient flows fully based on this template. We view this assumption reasonable because for model validation, the average patient wait times across all different scenarios (days) should be close to the numbers from simulating the templated schedule, since there is extreme variability in the no-show rate and the urgent add-ons (for example, there are days, such as when there is a severe winter storm, where 50% of patients will not show up while there are other days where the schedule will be booked to 120% of capacity because of a great number of urgent add-ons). In addition, Modeling the full template enables us to accordingly propose policies and strategies for when the capacity of the clinic reaches its maximum utilization among regular days, which makes more sense from the perspective of policy deployment.

Table 2: The number and percentage of slots in the template for patients in each type as well as the values for the AM / PM sessions respectively.

	Total	**NP**	**RV**	**VF**	**PO**	**LA**	**UR**	**AM Session**	**PM Session**
Number	80	8	30	27	11	3	1	44	36
Percent	100%	10%	37.5%	33.8%	13.8%	3.8%	1.2%	55%	45%

Although patients are all assigned an appointment time, their actual arrival time may deviate from the assigned one. According to electronic health record data, patients come an average of 10.44 minutes early with a standard deviation (SD) of 19.78. To incorporate this variability in our model, we could not use a well-known distribution because none could be tuned to fit our data. Instead, we simulate this time deviation between patient's appointment time and arrival time based on normalized frequencies which we calculate directly from the electronic health record data.

Some patients will skip certain steps in the complete patient flow (Table 3). The value in each cell in Table 3 corresponds to the probability that patients in the specified type will complete each step during their visit. We calculate these values from the electronic health record data. For simplicity, we further assume that none of the LA patients will actually have a repeat evaluation by their attending physician after the intraocular pressure check, since this scenario rarely happens ($< 5\%$); we do not have sufficient data to estimate this rate or the corresponding processing time precisely.

Table 3: The probability of patients in each type completing each step respectively during their clinic visits.

	NP	RV	VF	PO	LA	UR
Check-in	1	1	1	1	1	1
Technician Exam	1	1	1	1	1	1
Visual Field Test	0.722	0.085	1	0	0	0
Dilation	0.61	0.223	0.435	0.071	1	0.4
Photography	0.754	0.138	0.371	0.012	0	0
Resident/Fellow Exam	1	1	1	1	0	1
Reg. Attending Exam	1	1	1	1	0	0.2
Laser Exam	0	0	0	0	1	0
Pressure Check	0	0	0	0	1	0
Check-out	1	1	1	1	1	1

The process time for different steps in clinic (with the exception of dilation, which takes an invariant 25 minutes) are all simulated by a log-normal distribution, which is a common distribution for modeling service durations for medical procedures (Berg et al. 2010; Erdogan and Denton 2013). Parameters of the log-normal distribution for each step in the clinic are further stratified by patient types, and are calculated based on the data collected from clinical operations over a 6-month period (January 5, 2018 - July 3, 2018) using RFID technology to conduct passive time-motion studies for patients and providers.

Transit time, the gap between the time when the resource(s) are available for the next patient and the time this patient starts the corresponding activity, is also taken into consideration in our study, as it takes time for both providers and patients to move between locations. Currently, this transit time is simulated as a bounded normal distribution (with min/max boundaries) with parameters based on the judgment of physicians and staff in the clinic.

We define patient wait time as the period that our patients are not accompanied by any care provider or staff after they check-in at the front desk. The only exception is the approximate one-hour waiting period for LA patients before they can have their pressure checked, which is treated as a special part of the laser procedure and thus is not added to their total wait times. All transit times are counted into patient wait times. We count transit time as patient wait time because the RFID passive time-motion studies count this time as wait time, and we want to be able to compare the RFID data and the simulated results directly.

For greater accuracy, we also incorporate patient flow through the retina clinic into our model in a rough 3-step procedure: check-in, stay, and check-out, since the usage of both check-in and check-out is shared between glaucoma and retina patients. We assume that the total number of patients visiting the retina clinic ranges from 50 to 130 with an equal probability, the arrival time is uniformly distributed from 7:20 AM to 3:40 PM, and the visit time (length-of-stay) follows a triangular distribution (min = 60, max = 120, mode = 80 minutes). These assumptions and parameter values are abstracted from the electronic health record and justified by discussion with clinic physicians and staff.

3.2 Model Validation

We verified the simulation model using the RFID time-motion study data. We compared the actual and simulated wait times. The results from the simulation model were found to be close to reality (taking both the no-show rate and the urgent add-ons into consideration). In addition, we verified the simulated clinic with our physician collaborator via visualizations of the waiting queues (see Section 4.3), and we agreed that the simulation model is accurate enough to evaluate and inform clinic policy changes.

4 COMPUTATIONAL RESULTS

In this section, we first present simulation results for the current-state scenario. We then provide a sensitivity analysis varying the number of residents and fellows available in the clinic to see patients. Next, we identify the bottleneck that causes the majority of patient wait time using visualizations of the waiting queues of different clinic resources. Lastly, a resource supplementation policy for reducing patient wait time is evaluated. We build our simulation model in Python (*version 3.6.5*) using the SimPy package (*version 3.0.10*), and all experiments here are simulated with 20,000 replications to ensure convergent results.

4.1 Current-state Scenario

We ran our simulation model using all inputs and parameters introduced in Section 3.1. We assumed there was 1 resident present during both the AM and PM session. Table 4 and Table 5 below show the mean and the standard deviation (SD) of patients' length-of-stay (LOS) and wait time, respectively, for their visits. The proportion of patient's wait time relative to their overall visit time was as follows: 38.23% for NP, 57.49% for RV, 48.59% for VF, 48.85% for PO, 49.50% for LA and 68.61% for UR. These results drove our motivation for proposing policies to reduce wait time and improve the quality of the healthcare service.

Table 4: Statistical summary of patients' length-of-stay (LOS) by each patient type.

LOS (minutes)	**NP**	**RV**	**VF**	**PO**	**LA**	**UR**
Mean	166.38	105.43	145.06	82.35	228.08	111.59
SD	47.54	36.24	41.87	33.44	30.28	30.60

Table 5: Statistical summary of patients' wait time by each patient type.

Wait Time (minutes)	**NP**	**RV**	**VF**	**PO**	**LA**	**UR**
Mean	63.61	60.61	70.48	40.23	112.91	76.56
SD	31.59	30.13	32.84	28.85	26.35	22.77

4.2 Sensitivity Analysis on the Number of Residents / Fellows

The number of residents and fellows available in the clinic varies day by day because they share their time between the clinic and the operating room, and this is different from other resources. If the operating room is very busy on a day, there may not be any trainees present in the clinic. Therefore, it is important for us to understand how this uncertainty impacts the simulation results. We tested the number of residents and fellows by varying them from 0 to 2 independently. Table 6 displays the corresponding wait time results.

These experiments show that patients' wait time did not fluctuate significantly when the number of residents and fellows changed. This conclusion matches our expectation, as a patient will do this additional exam only if there is one such trainee available at the time when this patient is ready to go to see his/her physician (if on the contrary there is no one available, the patient will skip this step and directly go to do/wait for his/her attending exam). Therefore, varying the number of these resources in the clinic should neither aggravate nor mitigate the congestion of the patient flows substantially. The very slight incremental increase in wait time as the number of residents/fellows grows is mainly caused by the transit time, because when this number increases, more patients are able to be examined by a trainee before their regular attending exams and the corresponding transit times for this additional step are counted as their wait times. Given

Table 6: The mean and standard deviation (SD) of patients' wait time by varying the number of residents (R) and fellows (F) present in the clinic.

Wait Time (minutes)		F = 0		F = 1		F = 2	
		Mean	SD	Mean	SD	Mean	SD
R = 0	NP	62.92	31.22	63.48	31.41	64.06	31.76
	RV	60.31	30.1	60.48	30.08	60.67	30.05
	VF	70.19	32.82	70.4	32.82	70.62	32.87
	PO	39.64	28.85	40.14	28.84	40.59	28.87
	LA	112.33	25.98	112.64	25.96	113.15	26.39
	UR	76.33	23.00	76.31	22.57	76.57	22.81
R = 1	NP	63.61	31.59	63.98	31.72	64.38	31.91
	RV	60.61	30.13	60.79	30.22	60.99	30.19
	VF	70.48	32.84	70.74	32.96	70.85	33.00
	PO	40.23	28.85	40.66	28.93	40.78	29.08
	LA	112.91	26.35	113.54	26.34	113.96	26.41
	UR	76.56	22.77	76.55	22.75	76.75	22.86
R = 2	NP	64.07	31.79	64.39	31.89	64.60	31.98
	RV	60.80	30.16	60.91	30.11	61.07	30.13
	VF	70.64	32.89	70.88	32.95	70.99	33.02
	PO	40.65	28.93	40.69	28.95	40.90	29.11
	LA	113.23	26.48	113.97	26.45	114.47	26.56
	UR	76.58	22.80	76.70	23.08	76.81	22.75

that our simulation model is not sensitive to these uncertain resources, for the rest of the experiments in this section, we assume that there is 1 resident available during both the morning and the afternoon sessions.

4.3 Bottleneck in Patient Flow

In order to reduce patients' wait time during their clinic visits, we need to identify the causes of wait time. We stratified the mean values of patient wait time by visit type and process step. The results from this simulation are listed in Table 7.

The majority of the wait time took place when patients were waiting for the technician exam. A smaller portion of the wait time occurred when patients waited for visual field tests, the attending/laser exam and the post-laser procedure pressure check. The wait time for all other steps was negligible, as it corresponded to transit time plus the 25-minute dilation time.

Figures 3, 4 and 5 visualize the waiting queue for requesting the technician resource, the medical assistant resource and the physician resource respectively. The x-axis displays the time of a day while the y-axis shows the average number of patients waiting for the corresponding resource. From these visualizations, we find the following:

1. The technician resource was in high demand at almost all times for both the AM and PM sessions, which resulted in a substantial patient wait time as shown in Table 7.
2. The number of patients waiting for the technician resource reached its peak of 10 patients waiting immediately after the clinic started operating at 7:30 am.

Table 7: The mean value of patient wait time stratified by different steps, where "-" means it's not applicable as no patients in the specific type will go through the specific step during their visits. Note that if a patient is determined to not go through a specific step, then this patient will not be counted into the calculation of the corresponding wait time for that specific step.

(minutes)	**NP**	**RV**	**VF**	**PO**	**LA**	**UR**	**Overall**
Technician Exam	30.45	41.70	40.54	26.58	63.59	61.90	39.18
Visual Field Test	4.92	6.53	5.62	-	-	-	5.57
Dilation	25.00	25.00	25.00	25.00	25.00	25.00	25.00
Photography	1.03	1.04	1.04	1.04	-	-	1.04
Resident/Fellow Exam	1.01	1.01	1.01	1.01	-	1.01	1.01
Attending/Laser Exam	12.30	11.37	11.75	10.52	17.23	16.65	11.71
Pressure Check	-	-	-	-	6.08	-	6.08
Check-out	1.01	1.01	1.01	1.01	1.02	1.02	1.01

3. Attending physicians did not have a lunch break, though there is a 1.5-hour gap between the AM and the PM session with no appointment slots in the appointment template. Attending physicians stayed in clinic for an average of 3 hours later than the last patient's appointment time.

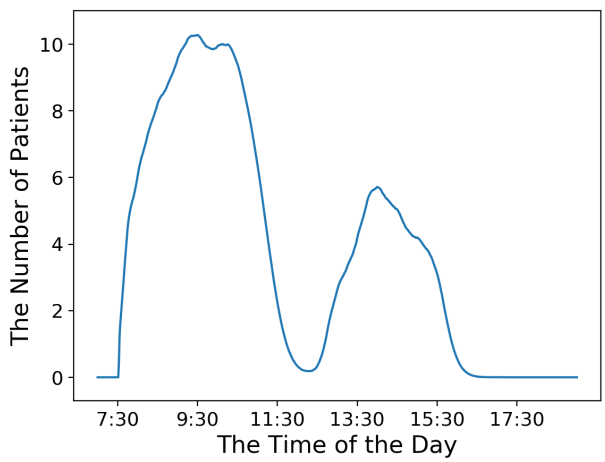

Figure 3: Average number of patients waiting for the technician resource.

From discussions with the clinic staff, we find that our findings match what technicians and physicians experience. For example, technicians usually find a crowd of people waiting in the main waiting area when they arrive in the clinic at 7:30 AM. Physicians report that they typically finish the last patient exam at 6:30 PM though the last patient is scheduled at 3:30 PM.

In addition, as the queue for the technician resource is consistently long across the whole day, we do not expect the wait time to be reduced significantly through a traditional approach like shifting slots in the templates without supplying extra resources. Therefore, we focus on testing alternative strategies for adding extra available resources (staff and corresponding examination rooms) to improve patient wait time.

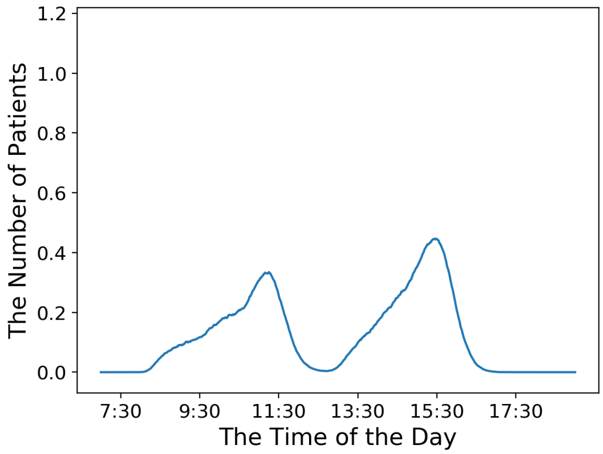

Figure 4: Average number of patients waiting for the medical assistant resource.

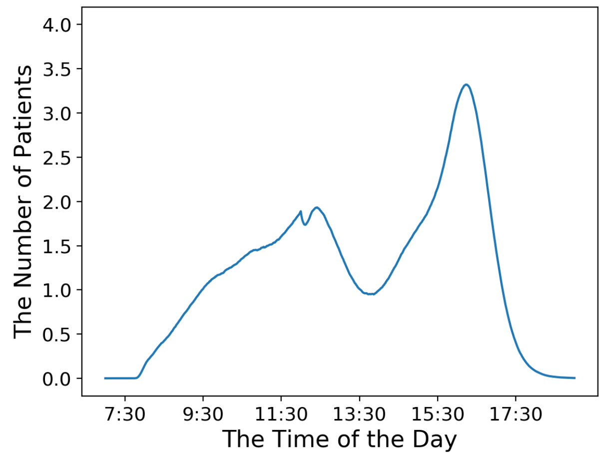

Figure 5: Average number of patients waiting for the physician resource.

4.4 Proposed Policy

As indicated in Section 4.3, the major portion of patient wait time occurs at the technician step of patient flow, and the technician resource is consistently in high demand throughout the clinic day. Thus, the most straightforward way to reduce the wait time would be increasing the number of the technician resources, i.e. hiring more technicians and equipping correspondingly more technician exam rooms. The glaucoma clinic at UM currently has 3 available rooms that could be converted into technician exam rooms. However, undertaking construction and hiring additional ophthalmic technicians is expensive. We use the model we developed here to do a series of what-if experiments, considering adding 1, 2 or 3 extra technicians and associated exam rooms, to help propose the most appropriate strategy.

From Table 8, patient wait time can be significantly reduced by increasing staffing by one technician with a corresponding exam room. It will further decrease if a second technician is added, in both cases without placing much more pressure on the rest of steps in the patient flow (see Table 9). For example, for an RV patient, wait time decreased by 18.56 minutes (30.6%) when one technician was added, by 27.46 minutes (45.3%) when two technicians were added, and by 31.41 minutes (51.8%) when three technicians were added. Considering the cost of deploying additional technicians, we conclude that adding 2 extra units of the technician resource would be the most efficient strategy for reducing patient wait time in the clinic. Figures 6, 7 and 8 provide the same visualizations of the waiting queues as above but with the number of the technician resources increased by two, which demonstrates that the peak number of patients waiting for the technician decreased from ten to four.

Table 8: The mean value of patient wait time in different type when there are 5, 6, 7 or 8 technicians present in the clinic respectively.

(minutes)	**5 Technicians**	**6 Technicians**	**7 Technicians**	**8 Technicians**
NP	63.61	55.20	50.86	48.22
RV	60.61	42.05	33.15	29.20
VF	70.48	55.70	48.47	45.01
PO	40.23	29.33	25.04	23.36
LA	112.91	76.01	58.40	54.79
UR	76.56	51.79	35.51	26.30

Table 9: The mean value of patient wait time for different step when there are 5, 6, 7 or 8 technicians present in the clinic respectively.

(minutes)	**5 Technicians**	**6 Technicians**	**7 Technicians**	**8 Technicians**
Technician Exam	39.18	20.97	12.01	8.33
Visual Field Test	5.57	7.44	8.94	9.54
Attending/Laser Exam	11.71	13.20	13.91	13.96
Pressure Check	6.08	4.34	2.66	1.79

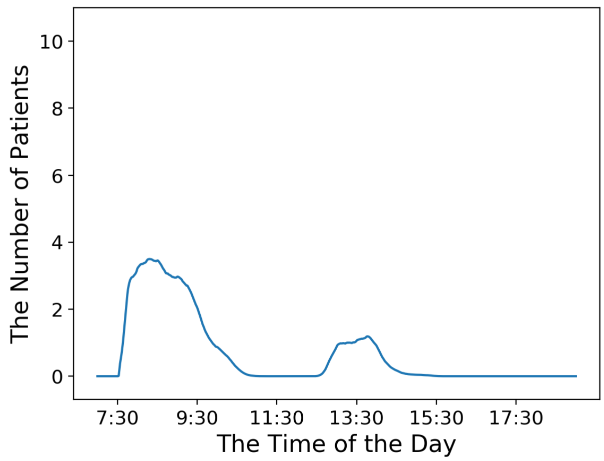

Figure 6: Average number of patients waiting for the technician resource when the number of technicians present in the clinic is increased to 7.

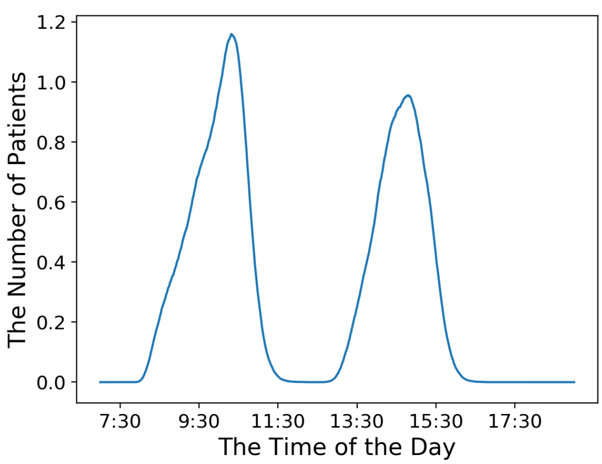

Figure 7: Average number of patients waiting for the medical assistant resource when the number of technicians present in the clinic is increased to 7.

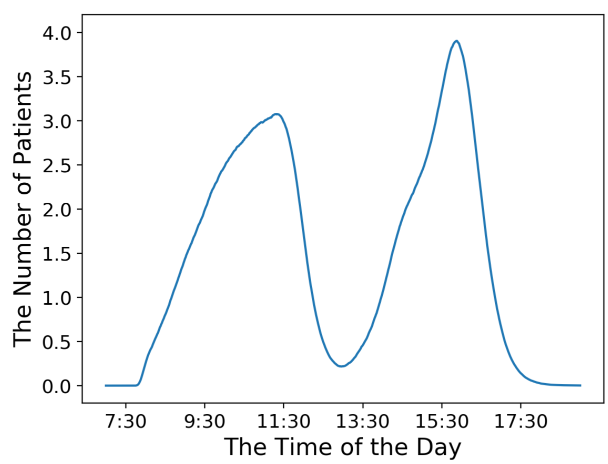

Figure 8: Average number of patients waiting for the physician resource when the number of technicians present in the clinic is increased to 7.

5 CONCLUSION

Through developing a discrete-event simulation model, we built a virtual environment to represent the actual daily operations of the glaucoma clinic at UM, where the input parameters were derived from electronic health record data and data collected by passive time-motion studies using RFID technology. A number of experiments were carried out to analyze the flow of patients during their visits, and we identified that the most significant current bottleneck in terms of patient wait time was the technician exam. We considered the possibility of adding one, two or three technicians and exam rooms, and implemented what-if experiments to evaluate their outcomes. We found that the clinic would benefit the most if two additional technicians were hired and two additional rooms were equipped, considering the trade-off between patient wait time and practice expense.

To improve the accuracy of our simulation model, we plan to do more provider shadowing in the clinic to collect data regarding the transit time between follow-up exams. Incorporating the no-show and late cancellation rate as well as the compensation from the urgent add-ons explicitly into our simulation model will be another important component of future work. We plan to use the electronic health record data to formulate these uncertainties in a precise manner. As increasing two extra units of technician resource provides sufficient room for further schedule adjustment, and the current workload is unbalanced between the morning session and afternoon sessions (see Figure 6), a potential next step will be evaluating switching slots in the current template to improve the resource utilization and further reduce patient wait time.

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REFERENCES

Babashov, V., I. Aivas, M. Begen, J. Cao, G. Rodrigues, D. DSouza, M. Lock, and G. Zaric. 2017. "Reducing Patient Waiting Times for Radiation Therapy and Improving the Treatment Planning Process: A Discrete-Event Simulation Model (Radiation Treatment Planning)". *Clinical Oncology* 29(6):385–391.

Barger, M. A. 2003. "Crossing the Quality Chasm: A New Healthcare System for the 21st Century.(Bookshelf)". *Healthcare Financial Management* 57(3):120–121.

Berg, B., B. Denton, H. Nelson, H. Balasubramanian, A. Rahman, A. Bailey, and K. Lindor. 2010. "A Discrete Event Simulation Model to Evaluate Operational Performance of a Colonoscopy Suite". *Medical Decision Making* 30(3):380–387.

Berg, B., G. Longley, and J. Dunitz. 2018. "Use of Simulation to Evaluate Resource Assignment Policies in a Multidisciplinary Outpatient Clinic". In *Proceedings of the 2018 Winter Simulation Conference*, edited by M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, 2646–2655. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Cayirli, T., E. Veral, and H. Rosen. 2006. "Designing Appointment Scheduling Systems for Ambulatory Care Services". *Health Care Management Science* 9(1):47–58.

Duguay, C., and F. Chetouane. 2007. "Modeling and Improving Emergency Department Systems Using Discrete Event Simulation". *Simulation* 83(4):311–320.

Erdogan, S. A., and B. Denton. 2013. "Dynamic Appointment Scheduling of a Stochastic Server with Uncertain Demand". *INFORMS Journal on Computing* 25(1):116–132.

Günal, M. M., and M. Pidd. 2010. "Discrete Event Simulation for Performance Modelling in Health Care: A Review of the Literature". *Journal of Simulation* 4(1):42–51.

Guo, M., M. Wagner, and C. West. 2004. "Outpatient Clinic Scheduling: A Simulation Approach". In *Proceedings of the 2004 Winter Simulation Conference*, edited by R. G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, 1981–1987. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Harper, P. R., and H. Gamlin. 2003. "Reduced Outpatient Waiting Times with Improved Appointment Scheduling: A Simulation Modelling Approach". *OR Spectrum* 25(2):207–222.

Jun, J., S. H. Jacobson, and J. R. Swisher. 1999. "Application of Discrete-Event Simulation in Health Care Clinics: A Survey". *Journal of the Operational Research Society* 50(2):109–123.

Lee, B. W., Y. Murakami, M. T. Duncan, A. A. Kao, J.-Y. Huang, S. Lin, and K. Singh. 2013. "Patient-Related and System-Related Barriers to Glaucoma Follow-Up in a County Hospital Population". *Investigative Ophthalmology & Visual Science* 54(10):6542–6548.

Leiba, A., Y. Weiss, J. S. Carroll, P. Benedek, and Y. Bar-dayan. 2002. "Waiting Time Is a Major Predictor of Patient Satisfaction in a Primary Military Clinic". *Military Medicine* 167(10):842–845.

Liang, B., A. Turkcan, M. E. Ceyhan, and K. Stuart. 2015. "Improvement of Chemotherapy Patient Flow and Scheduling in an Outpatient Oncology Clinic". *International Journal of Production Research* 53(24):7177–7190.

Norouzzadeh, S., N. Riebling, L. Carter, J. Conigliaro, and M. E. Doerfler. 2015. "Simulation Modeling to Optimize Healthcare Delivery in an Outpatient Clinic". In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 1355–1366. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Pan, C., D. Zhang, A. W. M. Kon, C. S. L. Wai, and W. B. Ang. 2015. "Patient Flow Improvement for an Ophthalmic Specialist Outpatient Clinic with Aid of Discrete Event Simulation and Design of Experiment". *Health Care Management Science* 18(2):137–155.

Prum, J. B., L. F. Rosenberg, S. J. Gedde, S. L. Mansberger, J. D. Stein, S. E. Moroi, J. L. Herndon, M. C. Lim, and R. D. Williams. 2016. "Primary Open-Angle Glaucoma Preferred Practice Pattern (R) Guidelines". *Ophthalmology* 123(1):P41–P111.

Quigley, H. A., and A. T. Broman. 2006. "The Number of People with Glaucoma Worldwide in 2010 and 2020". *British Journal of Ophthalmology* 90(3):262–267.

Rohleder, T. R., P. Lewkonia, D. P. Bischak, P. Duffy, and R. Hendijani. 2011. "Using Simulation Modeling to Improve Patient Flow at an Outpatient Orthopedic Clinic". *Health Care Management Science* 14(2):135–145.

Yip, K., S.-K. Pang, K.-T. Chan, C.-K. Chan, and T.-L. Lee. 2016. "Improving Outpatient Phlebotomy Service Efficiency and Patient Experience Using Discrete-Event Simulation". *International Journal of Health Care Quality Assurance* 29(7):733–743.

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