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Reducing patient wait times and improving resource utilization at British Columbia Cancer Agency's ambulatory care unit through simulation

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Abstract We consider an ambulatory care unit (ACU) in a large cancer centre, where operational and resource utilization challenges led to overcrowding, excessive delays, and concerns regarding safety of critical patient care duties. We use simulation to analyze the simultaneous impact of operations, scheduling, and resource allocation on patient wait time, clinic overtime, and resource utilization. The impact of these factors has been studied before, but usually in isolation. Further, our model considers multiple clinics operating concurrently, and includes the extra burden of training residents and medical students during patient consults. Through scenario analyses we found that the best outcomes were obtained when not one but multiple changes were implemented simultaneously. We developed configurations that achieve a reduction of up to 70% in patient wait times and 25% in physical space requirements, with the same appointment volume. The key findings of the study are the importance of on time clinic start, the need for improved patient scheduling; and the potential improvements from allocating examination rooms flexibly and dynamically among individual clinics within each of the oncology programs. These findings are currently being evaluated for implementation by senior management.

Keywords Simulation · Health care · Ambulatory clinic · Outpatient · Process improvement

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1 Introduction

This study was undertaken to address significant and increasing challenges regarding the use of space and resources in the Ambulatory Care Unit (ACU) in the Vancouver Centre (VC) of the British Columbia Cancer Agency (BCCA). Physicians' office space, clerical support and examination rooms were often in short supply at times of peak volume leading to overcrowding, delays, and concerns regarding patient safety. Further, patient volumes are anticipated to increase in the future as the population ages.

The BCCA provides a province-wide, population-based cancer control program for the residents of British Columbia and the Yukon, Canada. The Vancouver Centre (VC) is the largest of the five BCCA regional cancer centres, and is the referral facility for several specialized provincial programs. The VC has the largest patient volume of all BCCA centres. In 2007/08, 41% of the 14,000 provincial cases treated by BCCA received care at the VC. Under BCCA's model of care, the ACU is the primary point for physician–patient contact. The three cancer programs (medical oncology, radiation oncology and surgical oncology) conduct patient appointments within the ACU. Appointment types include new patient, follow-up and cross program consults. Average volume at the VC ACU was 200 patient visits per day during 2007/08.

The ACU also serves as an academic teaching and research environment. BCCA professionals train significant numbers of medical students, residents and fellows, as well as students and interns from many other disciplines. In addition, an increasing number of patients participate in clinical trials, which results in heightened demand for space and staff. ACU appointments are often complex and involve oncologists, residents and medical students, in

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addition to other clinicians including nurses, dieticians and counsellors. (We will use the term *physician* throughout this paper to refer to any interaction with either an oncologist, a resident, or a medical student. When the interaction refers specifically to the oncologist, resident or student in particular, we will indicate it as such.)

In this paper we consider several operational characteristics of a cancer care outpatient service; most of which have been studied before, albeit in isolation. Instead, we analyze the *simultaneous* impact of scheduling, operational, and resource allocation changes on system performance. Further, our study is distinguished by the added complexity of managing the concurrent operation of several clinics, and the training of fellows, residents and medical students during patient consults. With an increasing trend towards the use of ambulatory care facilities to provide health care services efficiently, we believe this study is particularly timely.

2 Related literature

Our literature review focuses on booking and scheduling, patient and physician interaction, and examination room allocation. Because of the characteristics of the processes under analysis, including complex patient flows and considerable variability, we gave special attention to computer simulation models.

Simulation modelling has been extensively used to address a broad range of problems in health care settings. Jacobson et al. [1] provide a thorough overview of discrete-event simulation modeling applications to health care clinics and integrated health care systems over the last 40 years. They organize their survey in two areas: (1) optimization and analysis of patient flow, and (2) allocation of assets to improve the delivery of services. The first area covers patient scheduling, emergency room configuration, and physician and other health care staff scheduling. The second area considers bed, room and staff sizing and planning. They reference close to 180 studies reported in the literature, illustrating the variety of applications and how computer simulation is becoming more frequent in health care.

Applications of simulation to topics outside the more traditional area of patient flow and scheduling include Vos et al. [2], who consider the development of an efficient facility layout design for a new hospital, based on patient volumes while VanBerkel and Blake [3] and Comas et al. [4] focus on wait list management; the former addresses general surgery procedures and the effects of redistributing beds between sites, while the latter considers elective cataract surgery, an outpatient procedure, based on a prioritization system. Chan et al. [5] models the transcription activities in a medical records department, where the flow units are transcription jobs instead of patients.

Our study assesses an outpatient facility and addresses issues in both of the categories described by Jacobson et al.; improved patient flow through better appointment scheduling, and examination room capacity and allocation. The body of literature on outpatient (or ambulatory) studies is significant, with special emphasis on appointment scheduling. Bailey [6] reports one of the first studies on scheduling appointment rules focused on patient wait times. Cayirli and Veral [7] provide a comprehensive review of the literature on this particular aspect.

Liu and Liu [8, 9] address two factors related to our study that are not usually considered in the literature. A common assumption is that there is one punctual medical doctor in a clinic. However, in many cases, including ours, physicians are often late in arriving to their clinics. In addition, some outpatient clinics are served by a number of physicians performing identical functions, becoming a multi-server system. Liu and Liu consider these issues by assuming that there is a random setup time (lateness) for each physician, resulting in a random number of physicians (variable capacity) available during the early period of the clinic. Under this assumption, this system cannot be effectively handled with traditional queuing models. An important difference between these studies and our situation is that patients are scheduled to see their particular doctor. Although there are several physicians with similar characteristics, under BCCA's model of care patients are assigned to one specific oncologist who oversees care during the entire treatment period, and therefore cannot be assigned to 'the first available doctor' from a pool of physicians for a given appointment. In the BCCA ACU setting, in addition to the oncologist other physicians (residents or medical students) may see the patient during an appointment. This varies from patient to patient depending on the number of physicians in the clinic, thus randomly increasing the duration of the appointment for each patient. Still in this case, residents and medical students are pre-assigned to participate in an oncologist's clinic, and therefore the modelling approach presented by Liu and Liu does not directly apply.

In early studies, physician time was considered more valuable than patient time. Thus, the main objective was to use the physician's time most efficiently, scheduling patients to reduce idle time, usually at the expense of an increase in patient's wait time. More recently, patient time has gained more importance, requiring more balanced objectives.

The majority of the published empirical research is applied to a specific case, or assumes specific process distributions. Therefore, conclusions cannot be directly generalized to other situations involving different settings, such as other arrival patterns, appointment durations, or mix of patients.

Some studies are specific to cancer care. Among others, Sepulveda et al. [10] report their work at M. D. Anderson Cancer Center in Orlando, FL, a full-service cancer treatment center. Their objective was to analyze patient flow throughout the unit, evaluate the impact of alternative floor layouts, using different scheduling options, and analyze resource and patient-flow requirements for a new building. Baesler and Sepúlveda [11] present a case study with a simulation model integrated to a multi-objective optimization heuristic to find the best combination of control variables, considering four performance measures for a cancer treatment center facility. More recently, Matta and Patterson [12] address the problem of evaluating multiple performance measures in simulation experiments of outpatient clinics, a research motivated by The Division of Medical Oncology at the Duke University Medical Center (DUMC).

A large number of simulation studies in health care settings report on the difficulty of obtaining the required data to support modelling efforts such as this one, similar to the situation we faced. Carter and Blake [13] describe, through four different practical examples of using simulation to analyze a problem in an acute care hospital, the obstacles that were encountered and the lessons learned. They report a series of challenges, including completeness, comprehensiveness, reliability, contemporariness and unavailability of standards. White [14] reviews data sources used in simulation studies in health care and suggest alternative sources of data. Isken et al. [15] describe an approach for data collection using sensor networks in health care clinics, and Takakuwa and Katagiri [16] report on a simulation study developed using a series of data from terminal units and of test/inspection terminals as well as electronic medical records.

3 ACU process and clinics

Patients come to the ACU to see a specific oncologist on a scheduled appointment basis. These appointments are booked in advance, based on both the oncologist's schedule and the patient needs and availability. Figure 1 depicts the patient journey in the ACU during a typical appointment. Although variations occur depending on the needs of the patients, the process in the ACU can be described as follows:

(a) The patient arrives at the ACU and checks in at the reception. This event is recorded in the booking system and is visible to nurses and physicians through the information systems.
(b) The patient goes to the waiting room and remains there until called.
(c) A nurse or volunteer takes the patient into an examination room, fills in basic information such as weight and overall status in the patient record, and then leaves the chart in the physician office.
(d) The patient waits in the room for consultation.
(e) A medical student, resident, fellow or oncologist enters the room. There could be one or multiple patient–physician interactions.
(f) For multiple consults, the patient waits for the next physician to arrive, the subsequent consults take place, and then the patient leaves the room.
(g) If patients need to wait for future appointments to be booked or additional services, they return to the waiting area before being told they can leave the ACU. Physicians return to their office to dictate and prepare orders for future appointments and tests, which then go to the nursing station to be processed. After orders are completed, a nurse sees the patient, hands over the appointment card and discharges the patient from the ACU. Further nursing activities including patient education and medication injections may subsequently take place in nearby nursing assessment rooms.

Besides regular appointments, add-ons may occur when a patient has to be slotted in a particular day with a full schedule. In this situation, an add-on case is entered in the schedule (subject to the oncologist's approval) at the same time of a pre-existing appointment for another patient, creating a double-booking. Add-ons might be booked in any part of the schedule, usually

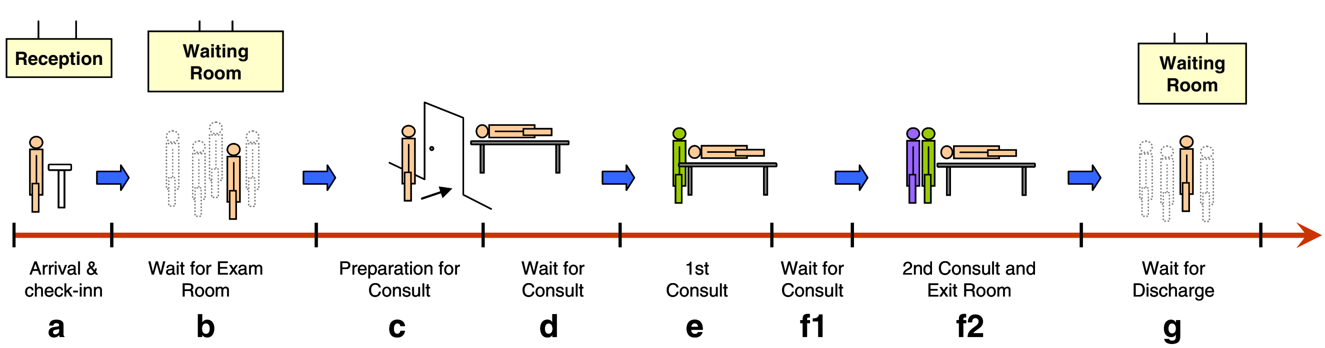


Fig. 1 Patient process for an ACU appointment

depending on patient preference. These appointments follow the same process as typical ACU appointments.

Patients may also have other appointments in the cancer centre before and/or after the ACU consult. Usually blood and diagnostic imaging tests are required before seeing the physician. Backlogs in other departments may interfere with the ACU process by delaying the arrival of the patients (or their corresponding test results).

On a typical day, between 15 and 25 different clinics run simultaneously within the ACU. Each clinic is run by an oncologist, and may also include the participation of a medical student, a resident, or a fellow. The configuration of these clinics, in terms of the number of physicians involved and the number and type of patients that are scheduled, varies on a daily basis. In general, clinics have regular scheduled hours every week with pre-defined appointment slots for different patient types. Variations to the schedules occur when physicians are away or in case of urgent cases.

Clinics from each of the three oncology programs function in separate although adjacent areas in the ACU. Every program is assigned its own set of examination rooms, a nursing station and clerical staff. There are 45 examination rooms in total: 24 are allocated to the medical oncology program, 16 to radiation oncology, and five to surgical oncology. The space is organized in *pods*, usually consisting of five examination rooms and one physician room. Figure 2 depicts the existing ACU floor plan.

Everyday ACU managers distribute the available examination rooms among the scheduled clinics. They do this 1 day in advance, based on the total number of clinics and physicians functioning that day, the volume and type of patients in each individual clinic, and staff availability. Usually students, resident and fellow activity are scheduled on the day of the clinic and cannot easily be planned for in allocating time slots for patients.

As a general rule, each clinic has two examination rooms. This allows for an efficient use of the physician's time as it avoids situations where they are forced to wait for the next patient because of room/patient unavailability due to room turn-around and/or patient preparation. In the simplified case of one physician and no turn-around times, two rooms allow the physician to go without interruptions from one patient to the next—assuming patients are placed and prepared in the rooms in a timely manner. If a clinic consists of the oncologist plus another physician, then two rooms might not be enough, especially if they operate in parallel. A similar situation occurs when patient-preparation times are considerable and there are several, short-duration appointments scheduled in a clinic, resulting in physicians being idle between patients (we should note that being idle is with respect to direct patient care; physician idle time may still include activities such as medical student teaching, responding to emails or pages, phone calls, or editing electronic patient reports). Conversely, clinics with one physician, fewer patients and longer appointments may not need more than one examination room.

The configuration of rooms into pods is to some extent restrictive, in that coordination becomes more difficult if a physician is assigned two rooms in different pods. In practice, ACU managers try to assign physicians examination rooms located in the same pod. As a result, the allocation of examination rooms to clinics has the potential to cause delays for patients or excessive idle time for physicians. The right balance depends on the total patient workload and resources available in the entire ACU.

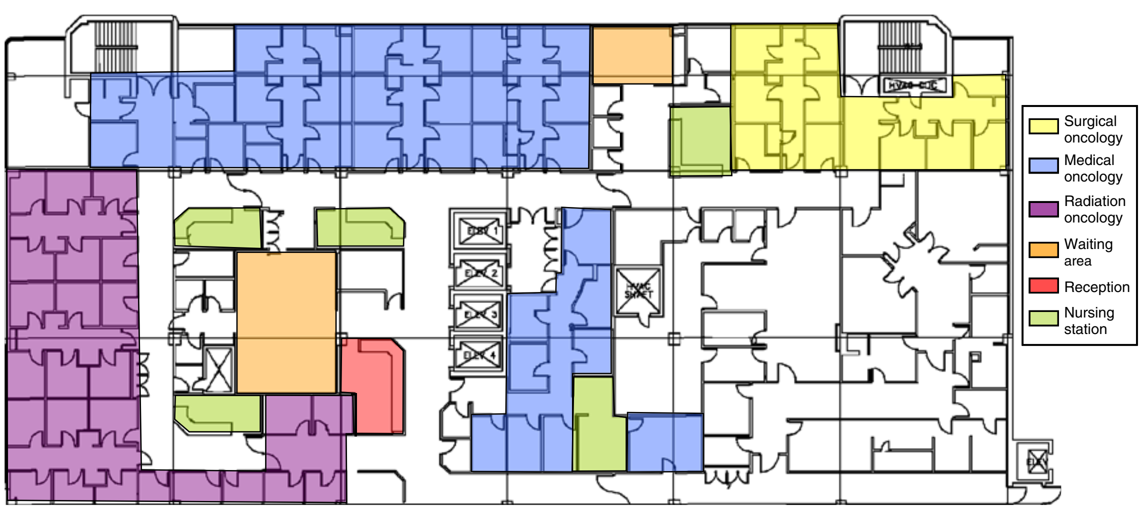


Fig. 2 Floor plan of VC's ACU and areas by oncology program

4 Analysis and model

4.1 Preliminary data analysis

To determine potential areas of improvement, we performed comprehensive process and data analyses. The primary data source was the appointment booking system, which contains scheduled appointment information for all patient visits, in particular those to the ACU. Patient volumes by time of the day, day of the week, and month were analyzed at different levels: overall ACU, by program (medical, radiation and surgical oncology), by visit type (new patients, follow-ups, consults) and by tumour site clinic (e.g., breast, lung, etc.). Table 1 provides a summary of average daily appointment volume and scheduled appointment duration by oncology program and appointment type.

Unfortunately, but not at all an unusual situation in health care, available data were not sufficient to determine process and wait times for all the stages shown in Fig. 1. Existing information systems record only booking data for appointments. They exclude more detailed information on the processes, such as time stamps for arrival and physician–patient interaction, and performance metrics of the system such as delays, idle time, overtime and room occupancy.

Considering the limitations of the existing data, it was apparent that a time study was required to obtain more detailed data.

4.2 Time study

The objective of this data collection study was to obtain the necessary information to measure patient wait times, appointment duration, and utilization of resources such as examination room and physicians.

Through observation of the system and interviews with ACU staff, we first developed a high-level process map (Fig. 3) of the appointment visits and identified the key points in time we needed to measure based on our observations and experience with the clinic processes. We then used this information to design the data collection process, determining how many surveyors would be required and where they should be physically located. We sampled and observed a number of ACU clinics during the course of several days, capturing process times for over 600 patient visits. We believe this data is unique and provides considerable insight to the patient experience and resource utilization.

Using the collected data we reconstructed the different stages in the ACU process for each patient. We also linked the data to other information systems to append appointment information including patients' cancer site, type of visit and appointment time to the process-data.

With all this information, we summarized patient arrivals, physician–patient interactions, chart/order preparation, turn-around times and waiting times by program and visit type.

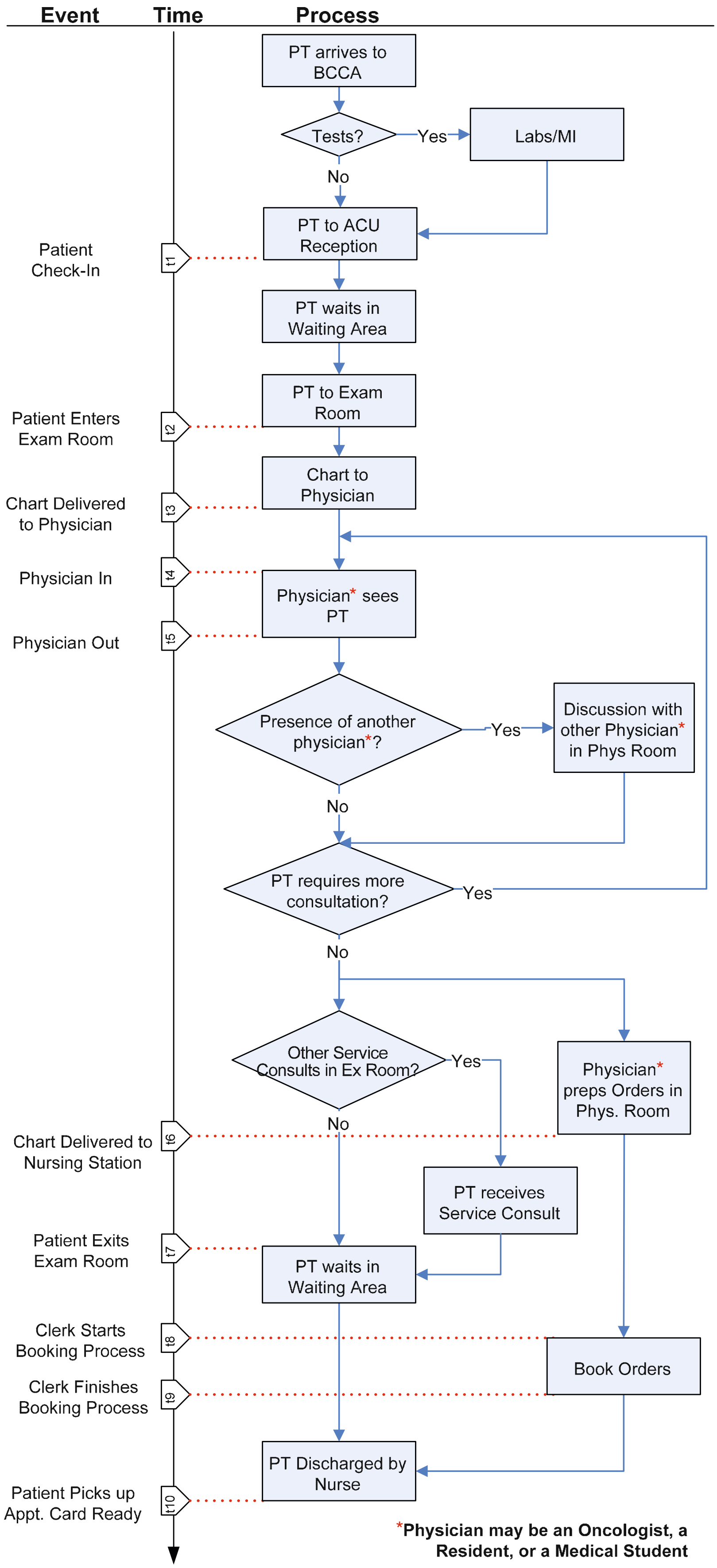
The analysis of the collected data shows that:

- Most patients arrive on time to their ACU appointments (78% check-in before the scheduled time; only 10% arrive more than 10 min late).
- About 6% of patients fail to show for their appointments.
- Patients wait on average 14 min from their scheduled appointed time until they are first seen by a physician in the examination room. About 10% of patients wait more than 44 min.
- When a resident or medical student is involved, total direct physician–patient interaction time nearly doubles, significantly extending room utilization.
- For some appointments, booked durations differ significantly from the time required for the entire visit. Underestimated appointment durations result in delays for the clinic, while overestimates cause physician idle time.
- Half of the sampled ACU clinics started more than 7 min late, with about 10% being more than 23 min late.
- On average, ACU examination rooms are empty 60% of the time; a patient and a physician were in the room 20% of the time and 20% of the time a patient (and family) was in the room with no medical professional present. Figure 4 shows a typical pattern of examination room utilization by patients and physicians.

Table 1 Average daily appointment volume and scheduled appointment duration by oncology program and patient type

	Radiation oncology		Medical oncology	
Appointment type	Avg. appts. per day	Avg. sched. duration (min)	Avg. appts. per day	Avg. sched. duration (min)
New Patient (*N*)	13.5	53.6	8.6	57.2
Consult (*C*)	5.6	31.7	6.3	55.8
Follow Up (*F*)	43.5	14.5	104.9	16.3
Total	62.7	24.5	119.8	21.3

Fig. 3 ACU process map with time stamps to record in data collection



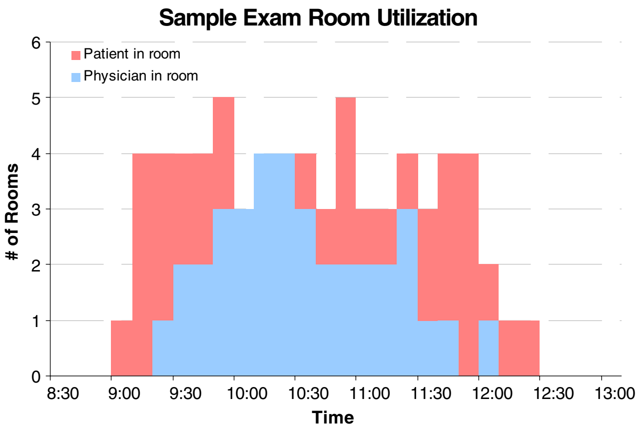


Fig. 4 Example of exam room utilization for a five-room pod

The collected data provided great insight into the process, and helped identify areas to explore for opportunities for improvement. Excessive process times, unnecessary wait times, and low resource utilization served as indications on where to focus our analyses.

In particular, patient wait time data provided new insights into the patient experience. Because physicians and staff were only involved in parts of the process, their previous impressions of the patient experience were imperfect and subjective. This new data provided enough information to build statistical distributions of process and wait times for all the stages in the ACU process. It also produced an understanding of what patients experience ‘on average,’ what the worst case scenario (depicted by the 90th percentile) looks like and how frequently it occurs.

We shared our data analysis results with physicians and other ACU personnel to validate our understanding and interpretation of the process, and to gather additional input not reflected in the data that could help us redesign operations.

4.3 Simulation model

Considering the characteristics of the ACU process, we decided to use discrete event simulation, and developed a model using the Rockwell Arena (version 11) software.

The model encompasses patient flow from arrival to departure from the examination room, seizing limiting resources such as oncologists and examination rooms. It incorporates the randomness and variability present in all stages of the process, including patient arrivals, consult durations, and other process times. Concurrent clinics from radiation and medical oncology are included in the simulation model. This translates to a maximum of 25 clinics and 45 examination rooms operating simultaneously.

A significant difference between our model and those reported in the literature is the consideration of multiple independent clinics operating simultaneously. This better represents the real process, especially when considering resources that are shared among several clinics, such as examination rooms and waiting area. Another important difference is the inclusion of more than one physician, residents and medical students in addition to oncologists, as part of the process. The role of residents/students is different to that of oncologists, and thus not interchangeable as in the case of a clinic with a pool of similar physicians. This is very relevant in an academic environment, such as the one studied in this paper, because overall process times and resource requirements increase due to the additional physician–patient interactions.

Residents and medical students are common within the ACU. Their involvement in the clinic ranges from shadowing oncologists, to assisting oncologists with patient information retrieval, to actual consultation and diagnosis. Residents and students are not present during every oncologist’s clinic. However, when they are present, they work with oncologists on several cases spread over the duration of the clinic. The selection criteria of cases for residents and students can vary depending on their skill level and oncologist preferences. Also, residents and students in some cases support the oncologists by consulting a patient on their own. This enables the oncologist to consult another patient simultaneously. Therefore, more than one patient can be interacting with a physician in a clinic at any given time. All these factors need to be incorporated into the simulation model.

During our data collection process, it was difficult to distinguish between residents and students. Therefore, we modelled both residents and students as one resource type. To incorporate this resource into the simulation model, we first probabilistically determine for each clinic whether a resident/student will be working or not. If a resident/student is present, the patients in the clinic would then have a probabilistic chance of encountering a student/resident. We obtained these probabilities from the collected data. Our analysis of the patient paths showed that multiple sequences of patient–physician interaction occur when resident/students are involved in seeing a patient. For certain instances, a resident/student may consult with a patient alone first, followed by another consultation with the oncologist and resident/student together. Other times, the oncologists would see the patient along with the resident/student in one consultation visit. We modelled the most frequently observed sequences as process paths in the model, outlined in Table 2. These paths are selected probabilistically, unique to program and patient type. Resources are seized according to the corresponding path for each patient, thus allowing instances where both a resident/student and an oncologist to consult different patients simultaneously.

Often fitting theoretical distributions is preferable than using empirical distributions since it allows for the simula-

Table 2 Patient–physician interaction pathways modelled considering oncologist and resident/student involvement

Pathway	First consultation	Second consultation
1	Resident/student	Oncologist
2	Resident/student	Oncologist and resident/student
3	Resident/student	None
4	Oncologist and resident/student	None

tion of events beyond the collected data. However, empirical distributions may be more appropriate when one does not want to lose important characteristics of the data, such as with bimodal distributions [17]. Triangular distribution may also be used when there is not sufficient data and a range and the most likely value of the distribution is known. In our study, we used theoretical distributions when our data had adequate fit (Kolmogorov–Smirnov p-value>0.05). When we encountered bimodal distributions and/or insufficient data points, empirical or triangular distributions were used. In the following paragraphs we describe the methods and fitted distributions (characterized by the type and corresponding parameters, such as mean (μ) and standard deviation (σ)) used to model some of the arrivals and processes.

The simulation model uses historical appointments to generate patient arrivals, specifying the type and appointment time of each patient arriving to the clinic. To capture the delay of patient arrivals to their appointment, we fitted a distribution to the observed time differences between the actual patient arrival and the scheduled appointment time. Patient arrivals to the model are then generated by offsetting the scheduled appointment time by this delay distribution. Normal distributions provided the best fit for both follow-up (μ=−13, σ=15) and consult (μ=−8, σ=13) visits. Notice that means are negative, indicating that patients on average arrive in advance. Similar delay distributions have been observed in literature [18, 19]. New patients, on the other hand, arrive considerably earlier (data shows strong positive skewness with $x = -26$ and S= 43). Commonly used distributions did not provide a good fit; we used a continuous empirical distribution to fully capture the arrival pattern of this category of patients.

We modelled clinic start times using a methodology similar to that for patient arrivals. The availability of both oncologist and student/resident resources at the beginning of the clinic is offset by a distribution of the observed time difference between the physician arrival and the first clinic appointment. These distributions are well approximated using a normal distribution for both oncologists (μ=8, σ= 8) and residents/students (μ=2, σ=8).

We fitted distributions to the service times of various process steps within the model, by patient type and program. Key process steps include: patient preparation time, physician interaction time, physician turnaround time, and time spent by the patient in the room after the consult. We selected the distribution with the best fit for each combination of process step, patient type and program. The physician interaction process step involving residents/ students comprises sub-processes that require fitting additional types of distributions. Due to the large variety of distributions used to model all these processes, we provide a general summary in Table 3.

Most of these distributions have been reported in previous outpatient simulation literature. These include service times modelled by Weibull [15, 20], gamma [21, 22] and log-normal [18, 23] distributions. In select cases where we used triangular and continuous empirical distributions, we performed sensitivity analysis. We found only limited impact on the results when these distributions were modified within reasonable ranges.

A majority of the queuing at the ACU follows a "first-in, first-out" rule. The assignment and placement of patients in the examination rooms however, is more complex. Patients first queue for a room before queuing for a physician. Because of variability and other previous appointments (such as labs), patients may arrive to the ACU substantially earlier than their scheduled appointment time. In some cases, patients may arrive even before the patient booked immediately prior to them. Under these circumstances, the early arriving patient is forced to wait until the appointment

Table 3 Summary of distributions used for various processes in the model

Process	Distribution
Patient preparation	Log normal, triangular, continuous empirical
Oncologist interaction (without resident/student)	Gamma, triangular
Oncologist and resident/student interaction	Triangular, continuous empirical, gamma, log normal, Weibull
Oncologist and resident/student turnaround	Normal, log normal
Patient in-room after consult	Weibull, triangular

time for the patient booked earlier has passed before queuing for a room. This ensures that patients who arrive on time are not penalized to wait due to patients that are scheduled later and arrive early. However, there is also pressure for nurses to fill examination rooms to minimize the possibility of physician idling. If a physician is available, and there is a free room and an early arriving patient waiting, then the patient will be placed immediately into the room. This logic is incorporated in our model to reflect reality.

ACU clinics have normal operating hours between 8:00 A.M. and 4:30 P.M. Under current practice, clinics will run overtime until all scheduled cases for the day are seen. There is no rescheduling of patients if clinics run late. Thus, from a modelling perspective, each operating day can be treated independently. All resources and patients in the system are reinitialized to zero at the beginning of each day. We simulate over a 1-month period, collecting statistics over multiple clinic days. There is no simulation warm-up time since the system, composed of individual clinics, never reaches steady state, and because we want to capture the clinic duration and all patient waits experienced for each day.

General assumptions of the model are that the clinics operate independently of others since there is no patient sharing between clinics. We assume that the probability of having a resident/student at a clinic is independent of other clinics. Also, we assume that the probability of having a resident/student for each patient case is independent of other patient cases. In reality, residents/students may be assigned a patient case conditional on their skill level and the state of the clinic (i.e. if it is running early or behind). All cancellations and add-on appointments are factored into the schedule by utilizing historical appointments that already incorporate those events. Patients queue for processes using "first-in first-out," except for the allocation of rooms. Service times are independent and identically distributed (i.i.d.), indicating that service times do not change if the clinic becomes increasingly congested. In reality, process times may be affected by congestion and delays. Observations of this dependency have been noted elsewhere [6, 20]. These assumptions were deemed acceptable by both clinicians and our team.

To evaluate the performance of each scenario, we used the following key metrics: patient wait time (average, percentiles), clinic end time, and physician idle time. In addition, resource utilization metrics including waiting room occupancy and examination room utilization were collected and analyzed.

We note that, in agreement with the literature [7, 18], we report patient wait time computed from the latest of the appointment time and the patient arrival. This prevents over- and under-estimating wait times when patients are early and late with respect to the appointment time, respectively.

Exploiting the graphical capabilities of the modelling software, we embedded the floor plan of the ACU in the simulation model and animated the entire appointment process as it occurred (Fig. 5). This helped to validate the model with physicians and staff as they were able to see what was happening real time as the simulation took place.

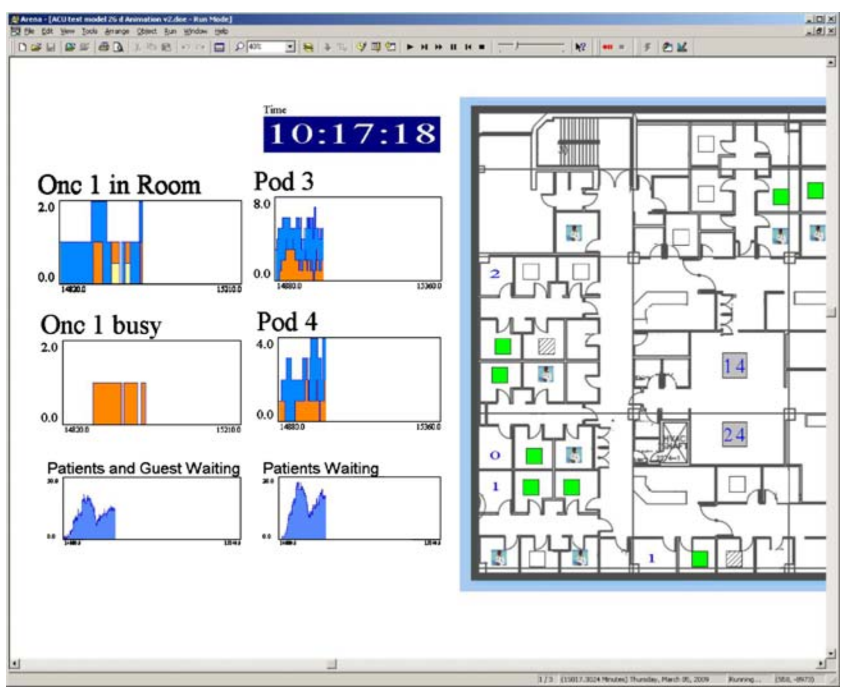


Fig. 5 Screenshot of the simulation model

4.4 Model verification and validation

We verified the operation of the model by tracing entities through the processes to ensure the model logic was correct. We tested extreme conditions to confirm the model performed as intended. We also consulted managers and physicians on summarized volumes and process metrics, to ratify high-level results. The animation of the ACU appointment process contributed significantly to ease of model verification and communication with key stakeholders.

For model validation we compared simulated output with collected data. We considered metrics that were independent of input parameters specified in the model, including average patient wait time until first physician, average total patient time in the system, average effective room utilization (ERU), and average total physician interaction time.

We constructed 95% confidence intervals for both the simulated and collected metrics. Table 4 shows a comparison between simulated and actual values, aggregated for the two major oncology programs.

With the exception of patient wait times in the medical oncology program, all simulated metrics fall within the 95% confidence interval of the actual data, suggesting that the simulation model accurately represents the ACU appointment process. The model slightly over-predicts wait times for medical oncology patients. Further analysis into the distribution of simulated and actual wait times indicates that a slightly longer tail exists in the simulated data. This tail may be attributed assuming i.i.d. processing time distributions. In actuality, when a clinic runs behind, physicians may decrease their consultation time to prevent excessive overtime and patient waits. Assuming i.i.d. in our model may result in an overestimation of wait times for patients during periods when clinics are running late. In addition, we assume i.i.d. probability for resident/student involvement. When a clinic is behind, oncologists may adjust the resident/student involvement to complete the clinic faster. Therefore, this factor may also contribute to an over prediction of wait times when there are delays in the clinic. These issues would apply to both programs, but since medical oncology has a higher patient volume per clinic, and a higher probability of resident/student interaction with patients, the impact on wait times of this assumption is higher for clinics in this program.

Other metrics potentially useful for validation purposes, such as physician idle time and clinic end time, were not actively captured during the data collection study, mainly due to observational problems (physicians located behind closed doors during most of the clinics hours). Because of this, we could not perform a direct validation of these metrics. We believe that since these metrics are inter-related to those we were able to compare, a successful validation of the listed metrics indicates that both physician idle time and clinic end time are reasonably representative as well.

5 Scenario analysis

Guided by the findings from the data analysis and the potential opportunities to use resources more efficiently, we developed a series of scenarios for evaluation through computer simulation to test the impact of changes in the processes on resource utilization and other performance indicators.

Overall, we ran and analyzed more than 100 scenarios. Each of them considers actual ACU appointments for a 1-month period, replicated 100-times to capture process variability. We selected 100 replications to obtain a 95% confidence interval of less than 0.3 min for both patient wait times, and clinic end times under all scenarios. We considered this level of confidence to be acceptable. The ability to distinguish differences between scenarios at a finer level would be negligible as we were interested in finding the major factors influencing wait times and clinic durations. We selected actual appointments from clinics in January 2008, the month with the highest patient volume over the past year, to test the model.

Table 4 Comparison of simulated and actual data over several key metrics for model validation

		Simulated		Actual	
Program	Metric	Mean	95% CI	Mean	95% CI
Radiation oncology	Patient wait time (min)	15.5	[15.1, 15.8]	14.5	[10.4, 18.6]
	Physician interaction time (min)	20.1	[19.8, 20.3]	20.1	[17.4, 22.7]
	Total time in system (min)	40.3	[39.8, 40.8]	38.6	[33.4, 43.7]
	Effective room utilization (%)	48.3	[48.0, 48.6]	49.4	[46.3, 52.5]
Medical Oncology	Patient wait time (min)	20.1	[19.7, 20.5]	16.8	[13.7, 20.0]
	Physician interaction time (min)	24.9	[24.7, 25.2]	26.0	[23.4, 28.5]
	Total time in system (min)	50.6	[50.2, 51.1]	46.8	[42.6, 51.0]
	Effective room utilization (%)	56.8	[56.6, 57.1]	56.5	[53.8, 59.3]

Each scenario is represented by a unique combination of levels for all the factors tested. We classified the factors in three groups: Operational, Appointment Scheduling, and Resource Allocation. Figure 6 shows all the factors and their corresponding levels as tested in the simulation model.

5.1 Operational factors

The purpose of the scenarios in this category is to quantify the impact of two factors related to the operations or processes of the system: the delay in starting the clinics, as identified during the time study, and the participation of residents/students in the clinics. Although it is evident that a late start of the clinics causes increased waiting times for the patients, the magnitude of its impact is difficult to estimate since patients may also arrive late for the appointments. Similarly, for the participation of resident/students in the clinics, rather than confirming the fact that additional physician–patient interaction instances increase the appointment duration, our objective is to quantify that effect for each oncology program.

The factors in this category are:

- Clinic Start: impact of clinics' start time on the performance of the system. We considered two levels: (i) distribution with mean 7 min late (current state), and (ii) distribution with mean zero (start on time).
- Resident/student: impact of resident/student involvement in the appointments. We studied two levels: (i) residents/students participate as per current rates (current state), and (ii) no resident/student involvement.

5.2 Appointment scheduling

In this category we group all factors that are related to different scheduling practices. The first factor in this group relates to having three different appointment types: New-patient (*N*), Follow-up (*F*) and inter-program Consult (*C*), all generally requiring the oncologists' consult. Each of these types have different duration and variability; new-patient appointments are the longest (about an hour long) and most variable, while follow-ups the shortest (15-min long) and less variable. The literature suggests that jobs with less variability should be scheduled first to reduce the overall completion time [23]. We wanted to test the applicability of that principle to our case. The second factor considers increased appointment durations, to test whether additional time per patient is required. The third factor in this category addresses the impact of additions to the schedule handled as double-bookings.

The factors and corresponding levels in this category are:

- Appointment Order: impact of scheduling appointments based on their duration and variability. We tested four levels representing alternatives of the order in which New-patient, Follow-up and inter-program Consult appointments are scheduled: (i) current order (non specific), (ii) increasing variability (*F*–*C*–*N*), (iii) decreasing variability (*N*–*C*–*F*), and (iv) low–high–medium variability mix (*F*–*N*–*C*).
- Appointment Adjustment: impact of increasing the time allocated for each appointment. We studied two categories:
  - Fixed Duration Increase: impact of increasing the time allocated for each appointment. We considered three levels: (i) current duration, (ii) 15% longer, and (iii) 30% longer.
  - Appointment Specific Duration Increase: impact of adjusting appointment times based on actual (sampled) visit duration, by appointment type and program. We evaluated two levels: (i) current state, and (ii) reschedule based on estimated physician turnaround duration.
- Add-ons to the Schedule: impact of add-on cases (double-bookings) in the schedule. We considered two levels: (i) add-ons scheduled any time in the clinic (current state), and (ii) add-ons scheduled at the end of the clinic.

5.3 Resource allocation

In this category we consider the way resources—examination rooms in particular—are allocated and used. As explained in the process description section, currently each clinic has one or more examination rooms dedicated exclusively to the physicians in each particular clinic. It is a known result from queuing theory that lower average wait

Factors and Levels Considered in the Scenario Analysis

Operational Factors		Appointment Schedulling Factors				Resource Allocation
Clinic Start	**Student/Residents**	**Appt. Order**	**Appt. Duration**	**Appt. Adjustment**	**Appt. Add-Ons**	**Exam Rooms**
Average 7' late*	Current practice*	Mixed*	Actual*	None*	Anywhere*	Dedicated*
Average on time	No student/resident	F-C-N	15% increase	Based on observed duration	Schedule at end of clinic	Pooled pod configuration
		N-C-F	30% increase			
		F-N-C				

(*) Represents current configuration of the system.

Fig. 6 Comparison of simulated and actual data over several key metrics for model validation times are achieved when multiple servers (the rooms in this case) are combined, instead of having several independent queues each with protected resources [24, 25]. In this group of scenarios we want to test the impact of having a common pool of examination rooms, where clinics are allocated rooms dynamically.

- Pod Configuration: impact of room allocation and room layout. Two levels were tested: (i) separate pods with dedicated rooms per clinic (current state), and (ii) pool pods with shared, flexible room allocation.

6 Results

Results from these scenarios show that there are opportunities to significantly improve processes in the ACU, increasing resource utilization and decreasing patient wait times.

Figure 7 shows the change in wait time (horizontal axis) and clinic duration (vertical axis) for the scenarios tested using the simulation model. The current state is located in the intersection of both axes (the origin).

Because the objective is to reduce the average wait time for patients, while reducing or not significantly increasing the clinic duration, the "best" points are in the lower left quadrant of Fig. 7. The set of non-inferior points (those that achieve the best performance in one metric for a given value of another metric) form the "efficient frontier."

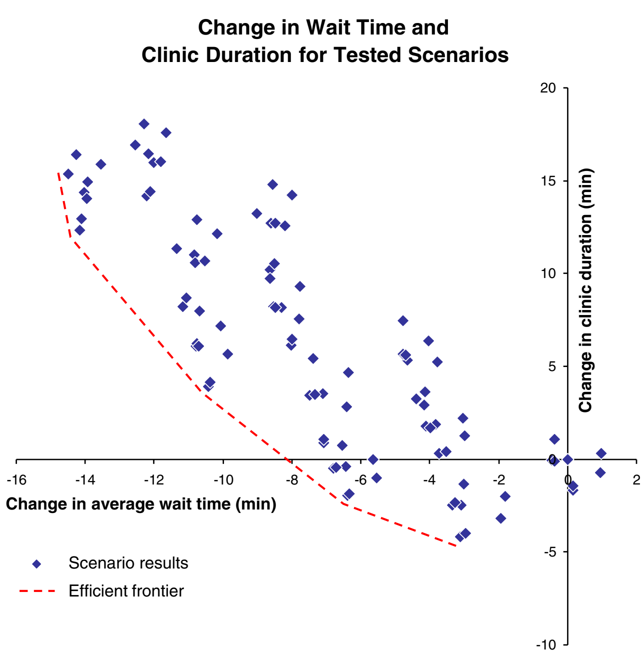


Fig. 7 Change in wait time and clinic duration. Points in the chart depict the performance for each scenario tested using the simulation model. The line connecting non-inferior solutions represents the efficient frontier

The scenarios with the best performance show a potential reduction of up to 70% in average wait time (from the current 21 to 6.4 min), while only increasing the clinic duration by 10%. Figure 8 depicts these results and their corresponding configuration factors. For instance, the best case in terms of wait time (rightmost) is achieved by: having clinics starting on time, increasing appointment durations by 30%, and scheduling add-ons at the end of the clinic.

Table 5 shows the patient wait time and clinic end time for the selected scenarios as the different factors are varied from current conditions. In addition to averages, we also evaluated the 90th percentile of wait times. For this measure, a potential reduction of up to 30 min in wait times is observed under the scenario with the largest improvement.

We performed independent univariate ANOVA tests over two metrics, patient wait time and clinic duration, considering the following factors in our scenario analyses: clinic start, appointment order, appointment duration, appointment adjustment, and appointment add-ons. We consistently found that all the levels within each factor were significantly different at 0.05 level and that interactions among factors were present, but significant only up to two-way interactions and of smaller magnitude than the main effects. We confirmed these results through MANOVA using both metrics as a multivariate response.

7 Discussion

Based on the findings from the initial data analysis, we focused our study on those components of the ACU process that cause delays or wait times. Delays in the start of clinics, excessive patient wait during the consult, and unnecessary

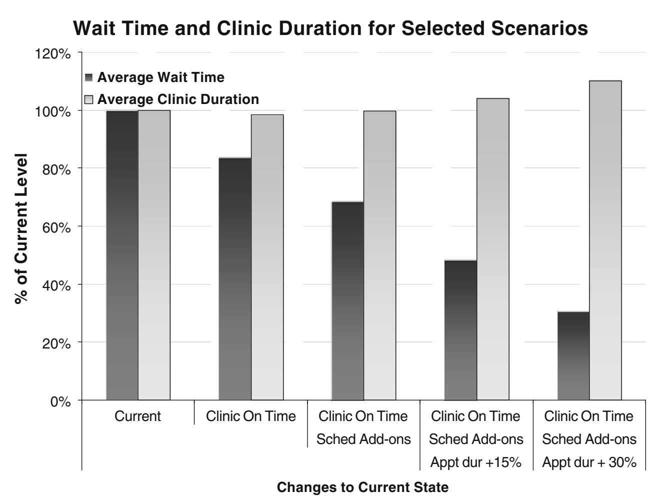


Fig. 8 Results from selected scenarios tested in the ACU simulation model

Table 5 Wait time and clinic duration results from scenarios tested in the ACU simulation model

	Scenario configurations				
	Current	Clinic on time	Clinic on time Sched add-ons	Clinic on time Sched add-ons Appt dur +15%	Clinic on time Sched add-ons Appt dur +30%
Average wait time	20.9	17.7	14.5	10.4	6.4
90th percentile of wait time	61.0	57.1	49.2	40.5	31.1
Average clinic duration	151.5	147.3	149.6	155.5	166.9
90th percentile of clinic duration	259.1	255.9	261.7	272.2	291.0

examination room utilization (such as when patients are purely waiting) are the main issues to be addressed. There are also many patients that have initiated their appointment but are waiting for additional steps in the process for their appointment to be finalized, extending the overall duration of their visit and deteriorating their experience.

The challenge is to find the mechanisms to reduce those unnecessary stages in such a complex system, and examine different scenarios. Our simulation model allowed us to take the next step and test a large number of individual and simultaneous changes in the processes and evaluate the resulting performance.

7.1 Findings from the simulation model

In terms of the individual factors tested using our simulation model, we found the following:

- Clinic Start: Results show that delays in starting the clinic have a significant impact on patient wait time as almost all appointments are affected by the late start. For the levels we considered in the scenarios, wait time could be reduced by 15% (3.1 min on average) if there was no delay.

Although it might seem evident that if clinics start late there will be increased wait times for the patients, its impact is not apparent, especially due to the effect of patients arriving late. It is also not clear how the clinic delay affects patients as the day progresses. Simulating different delay scenarios is an effective way to quantify the effect of this factor. Our results show that this is the single most important factor, and therefore worth exploring initiatives to reduce.

- Resident/student: Results from the simulation model considering a scenario where no residents or students are involved in the ACU appointments provide a comparison point to estimate the burden or cost that academic and teaching duties generate on the system.

When compared to the current situation, our analyses show a minimum change (10% reduction for medical oncology, no change for radiation oncology) in the number of examination rooms required if no resident/student participation occurs (and no other changes are considered). However, results show that average wait time actually decreases by up to 24% (5.3 min) for clinics in the medical oncology program in the case of no resident/student involvement (no change for clinics in radiation oncology).

- Appointment Order: After analyzing the different scenarios for this factor, no significant improvement has been identified by any particular configuration. This is because of the structure of ACU clinics, which comprise mostly Follow-up appointments (85% of the total, followed by 10% New-patients) and do not mix appointment types frequently (only 30% of the schedules have both Follow-up and New-patient appointments during the same clinic), making the appointment order less relevant.

In general, scheduling Follow-Ups first, with New-patients or Consults afterwards has little impact on wait times, but results in a slight decrease in total clinic duration. This result is consistent with the literature [23], which suggests that processing jobs with lower variability first achieves shorter completion times in general.

- Appointment Adjustment: Results show that only the fixed duration increase in the appointment time has a significant impact. This causes appointments to be scheduled further apart, reducing the probability of overlap and subsequent wait time. This reduces patient wait times by up to 43% (9 min reduction), while increasing clinic duration about 10%.
- Add-ons to the Schedule: A significant reduction in patient wait time can be achieved by booking add-on patients at the end of the schedule. Double booking appointment slots with add-on patients, especially early

in the clinic, results in delays affecting all subsequent patients. Booking all add-ons at the end of the clinic reduces patient wait times by 18% (3.8 min reduction), while increasing clinic duration only marginally (less than 1%).

- Pod Configuration: Using a more flexible approach to allocate examination rooms to physicians, such as a pool of shared rooms instead of the current designated rooms per clinic, significantly reduces the number of rooms needed to run the exact same number of clinics and patients.

Results from the simulation model show that if a pool of resources by program is used, up to ten examination rooms (six in the medical oncology program and four in the radiation oncology program) can be saved without significantly affecting patient wait time or other performance measure. This means that the equivalent of roughly two pods can be used for other duties, such as supplementary physician space, the operation of more clinics, or the expansion of adjacent areas.

Figure 9 shows the resulting average wait time for clinics in the medical and radiation oncology programs under a dynamic room allocation model (pod sharing), for different levels of examination rooms available by program. The current number of available examination rooms is 22 for medical oncology and 16 for radiation oncology; this sets the reference point for comparison. As the number of rooms in the pool is decreased in the simulation model, we observe no significant change in average wait time until six or more examination rooms are eliminated for medical oncology clinics, and four or more for radiation oncology clinics. The same effect is observed for other measures, such as clinic duration and physician idle time, and other metrics of the same measures (e.g., 90th percentile). At those points, the number of examination rooms available per program becomes the limiting resource in the system, causing clinic duration, physician idle time, and other measures to deteriorate compared to the current performance level.

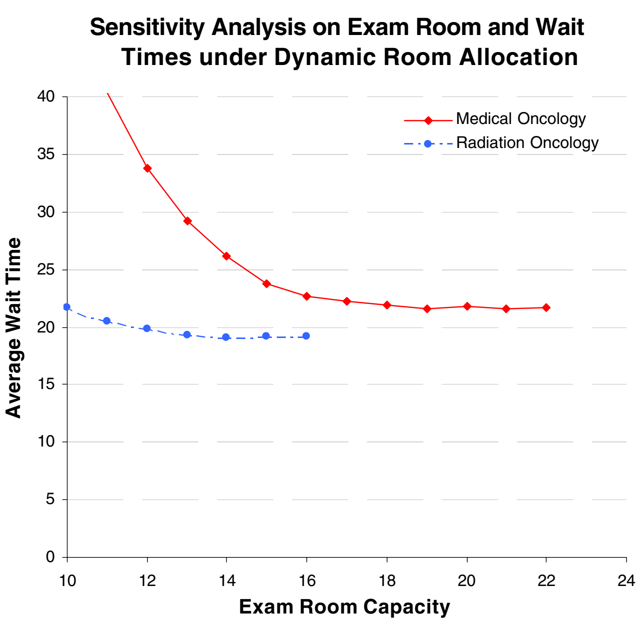


Fig. 9 Patient wait times versus exam room capacity under dynamic room allocation model

7.2 Finding the balance between patients and clinics

One of the challenges in studies like this one is finding the balance in efficiency for patients and clinics. Among other metrics we compute patient wait times and clinic overtime. These metrics are usually in conflict, in the sense that improving one degrades of the performance of the other. From the provider's perspective, maximum efficiency is achieved when there is no clinic overtime, which results in excessive wait times for patients. From the patient's perspective, minimum wait time is the ideal. The efficient frontier contains all the non-dominated solutions, and the challenge is to determine at which of these the system should operate.

One solution is to decide the overtime level we are willing to incur in the system, and accept the corresponding patient wait time from the efficient frontier. The problem of this approach is that we might be setting an unnecessarily low efficiency level for the clinics, even though patients could be willing to accept longer wait times.

An optional solution is to set the patient wait time to a given level, and calculate the resulting overtime for clinics. To obtain information about how long patients were willing to wait, and capture their perspective on other aspects of the ACU such as preference in place to wait, entertainment facilities and others, we designed and piloted a patient wait time survey. Although results obtained up to the time of writing this paper were only preliminary, important information was identified in terms of patients' preferences. In particular, findings from this survey suggest that the majority of patients consider a wait of 20 to 30 min reasonable. This can be used to find, from the simulation results, the range of overtime that operating at that level will cause.

Additionally, initial results from this patient survey indicate that, in general, patients prefer to wait in the waiting area rather than in the examination rooms. This supports the idea of delaying the time when patients are put into the examination rooms until strictly necessary, as in the scenarios that use the dynamic room allocation. Detailed results from the survey will be reported in a separate publication.

7.3 Data availability

One of the challenges we faced in this project was the lack of data in the form required to develop models such as the one we implemented. Based on our experience in similar projects with other health care organizations and other studies reported in the literature, this is a recurring problem. In most studies, data were collected primarily for costing purposes. More recently, the focus has been on the integration of clinical, imaging, order entry, and other information systems to implement electronic patient records.

Process-related information has received little attention; it is hardly measured, let alone stored in a data base/warehouse. The lack of data prevents the execution of in-depth studies based on advanced analytical methods such as those from the Operations Research field. Furthermore, having no baseline and post-implementation data inhibits the execution of a proper evaluation of the implementation of changes to the processes. This is an issue that needs to be addressed broadly in the health care sector.

8 Conclusion

The simulation model developed in this study provides valuable insight into the factors in the appointment process that can help reduce patient wait time and improve resource utilization.

Our main conclusions are the following:

1 To achieve significant improvements in terms of wait time reduction, a series of strategies need to be implemented simultaneously. There is no single action that results in a major reduction, but the combination of several strategies can cause a significant change (up to 70% reduction in our case).
2 The addition of flexibility to how rooms are currently allocated and utilized show promising results in terms of examination room capacity (up to 25% reduction in our case). Replacing the current 'dedicated' model for the allocation of rooms to clinics by a 'dynamic' paradigm that allows sharing rooms among different clinics can significantly reduce the number of rooms required to treat the same number of patients while preserving the performance standards to the patients.

Based on the findings from this study we have recommended the following high-level actions to improve the performance of this ACU:

(a) Promote clinic punctuality to avoid delays in the start of the clinic and efficient running of the clinic to reduce overtime;
(b) Allocate examination rooms more flexibly and dynamically among individual clinics within the medical, radiation and surgical oncology programs, to better utilize available capacity;
(c) Re-evaluate scheduling practices (for each physician) to ensure they accurately represent the type and duration of appointments being booked.

In addition, we recommend health care managers to collect process-related data systematically, both to allow the development of future decision-support models, and for monitoring and evaluation purposes of other initiatives.

8.1 Implementation

The recommendations proposed in this study are currently being evaluated for implementation by senior management. Some areas that will need to be addressed to carry out the recommended changes are:

- Start the clinic on time. To do this, patients, physicians and nurses need to be on time. Further, the required information, including patient records and test results, has to be available at the beginning of the clinic.
- Re-evaluate scheduling practices through analysis of individual physician practice patterns including the collection of accurate appointment durations for every patient category. A general policy to deal with appointment add-ons need to be implemented.
- Implement a flexible, dynamic room allocation within the existing physical space. This entails changes in the roles and responsibilities of nursing staff. It also requires the support of an IT solution to coordinate room allocation, indicating where patients are located, where a physician should go next, and the occupancy status of every examination room.

Process data should be collected on a permanent basis and stored in such a way that can be linked to other information systems. Collection of these data is not a simple task and will most likely require additional infrastructure and/or cultural changes to be sustainable, but the benefits of this information are invaluable. Ideally, the data collection system should be integrated to existing Health Information Systems (HIS) and be readily accessible to allow more informative reports to be developed. This will support both decision makers and operations researchers alike, enabling the development of advanced analytical models to find opportunities for improvement in the processes.

Collection of data is not something to delegate to the already busy staff in a clinic, especially if they are involved in clinical duties. Instead, this task should be accomplished incorporating technology that eliminates the burden on staff and significantly increases data accuracy and reliability. Sensors such as those mentioned by Isken et al. [15] or Saponas et al. [26] allow to capture data with minimal human interaction and with virtually no interference in the process. These applications are becoming more common in different health care setting [27], although not at the same pace as in the manufacturing sector.

In addition to gaining a better understanding of the processes in the ACU, this study contributed to disseminate among physicians and management the usefulness of operations research methodologies in aiding knowledge-based decision making.

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