Improving Patient Access in Oncology Clinics Using Simulation

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Abstract:

Purpose: Providing timely access is an important measure of patient satisfaction in specialty care clinics such as cancer centers. Excessive patient wait time to see an oncologist is very critical for cancer patients as they often benefit from starting the treatment process as soon as possible. This paper addresses capacity planning for both new and returning patients in cancer clinics. This research is motivated by a cancer center in Texas that seeks to improve its clinical performance to decrease new patient wait time to see an oncologist.

Design/methodology/approach: A simulation model is proposed to assess new patient access to oncologists when employing several tactical and operational policies such as resource flexibility, specialization flexibility, and reserving slots for new patients. The model utilizes two years of data collected from a cancer center in Texas.

Findings: The results suggest the best combination of operating policies in order to allocate patient demand to providers. This study also determines the required capacity level to provide timely access for new patients.

Originality/value: Although the literature in outpatient scheduling and capacity planning is rich, new patient access in oncology clinics has received limited attention. The few existing studies do not consider patient no-shows and cancellations, and to the best of our knowledge, no study addresses individual oncologist clinic flexibility and the idea of reserving slots for new patients.

Keywords: patient access, capacity planning, simulation, resource flexibility, oncology clinics

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1. Introduction

Cancer is recognized as one of the leading causes of death worldwide. According to estimates from the International Agency for Research on Cancer (IARC), the global number of new cancer cases is expected to increase annually (Bray, Ferlay, Soerjomataram, Siegel, Torre & Jemal, 2018). Therefore, if oncologists are not well utilized, or clinic capacity does not match with increasing demand, patients will have to wait an excessive amount of

time to see a provider. Also, well-established evidence indicates that delays in initiating cancer treatment are associated with tumor growth and, consequently, survival rates (Chen, King, Pearcey, Kerba & Mackillop, 2008; Fortin, Bairati, Albert, Moore, Allard & Couture, 2002; O'Rourke & Edwards, 2000). As a result, governments and healthcare systems are constantly attempting to provide timely access for new cancer cases by improving capacity planning and patient scheduling systems.

Oncology clinics are often challenged with scheduling a large volume of patients. One way to cope with increasing demand is to hire more oncologists. However, oncologists are expensive resources, and it takes time to hire them and have them start seeing patients. Thus, cancer centers seek operational strategies to maximize the utilization of their existing resources. This research is motivated by a Texas cancer center that seeks to decrease new patient wait time to see an oncologist.

In cancer centers, multidisciplinary teams (MDTs) are required for some cancer types to provide high-quality care and treatment for patients. Since MDTs are costly, oncology clinics try to reduce the number of days MDTs are required to be on service. Creating semi-flexible or fully dedicated clinics where oncologists only see certain cancer types in individual clinics is one way to reduce the costs of MDTs. To the best of our knowledge, the application of levels of resource flexibility has not been studied in the oncology scheduling literature. Therefore, one of the main contributions of this study is to investigate the effects of different clinic flexibility levels on new patient access.

Cancer patients follow various treatment plans depending on the tumor site and how advanced the cancer is. Each treatment plan generates a number of future appointments with oncologists. Most studies have focused only on new patients when studying patient access and have ignored returning patient demand for on-treatment and follow-up appointments. Therefore, another contribution of this study is to consider multiple on-treatment and follow-up visits to comprehensively analyze the impacts of the proposed policies. Oncologists' opinions and data from our collaborating cancer center are used to consider different treatment plans for different cancer types.

Patient no-shows and late cancellations are two of the main obstacles to the efficient utilization of capacity which further leads to delayed patient access (Samorani & LaGanga, 2015). Most studies regarding patient scheduling and capacity planning in cancer clinics ignore no-show and cancellation probabilities because they assume patients will show up for their appointments due to the critical nature of cancer. However, according to data from our cancer clinic collaborators, these probabilities are nonzero and therefore are considered in this research. Thus, another contribution of this study is to consider the uncertainties related to no-shows and late cancellations in patient scheduling. Moreover, according to the clinic data, no-show and cancellation rates depend on cancer types; for example, benign hematology patients tend to cancel or not show for their appointments more often than malignant hematology patients. Also, these rates differ in every stage of treatment; as patients move to follow-up visits, they are more inclined to not show for their visits. Therefore, different no-show rates for different cancer types and different treatment stages are considered in this study.

In most cancer clinics, oncologists are specialized in more than one cancer type. This overlap causes additional challenges for capacity planning because clinics should consider both the referral rate for each cancer type and the resource specialization to balance the workload across providers (Ma, Saure, Puterman, Taylor & Tyldesley, 2016). Consequently, empirical and ad hoc analysis methods and solution approaches are not adequate for efficient resource utilization. Rather, it is necessary to develop quantitative methods such as mathematical and simulation models.

Simulation models are one of the main methods commonly used to overcome the complexities and uncertainties found in outpatient scheduling and capacity planning problems. In this study, discrete event simulation is used to model patient scheduling and capacity planning in oncology clinics. The impact of several operating policies, including resource flexibility (also referred as clinic flexibility in this study), specialization configuration, and reserving slots for new patients are studied, and different scenarios are evaluated for each policy. Some of these operational characteristics have been studied before, albeit in isolation. This study aims to explore the simultaneous impact of multiple factors on new patient access to find the best combination of operating policies and the required capacity to provide timely appointments for cancer patients.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review relevant to our work. Section 3 provides a detailed problem description and explains the proposed simulation model. Numerical results and analyses are presented in Section 4, and several interventions are suggested. Finally, conclusions and opportunities for future research are discussed in Section 5.

2. Literature Review

Outpatient appointment scheduling is an attractive research area that has been widely studied since the seminal paper by Bailey (1952). Cayirli and Veral (2003), Gupta and Denton (2008), and Ahmadi-Javid, Jalali and Klassen (2017) provide a broad review of the literature on outpatient scheduling. Cayirli and Veral (2003) mainly focus on reviewing general problem formulations and modeling assumptions in previous studies, while Gupta and Denton (2008) concentrate on the most common types of healthcare delivery systems and challenging factors in appointment scheduling. Ahmadi-Javid et al. (2017) provide a comprehensive review of optimization studies on outpatient scheduling where a hierarchical structure is used to categorize the studies at the strategic, tactical, and operational levels.

Capacity planning in primary care clinics has been widely studied (Cayirli, Dursun & Gunes, 2019; Nguyen, Sivakumar & Graves, 2018; Qu, Peng, Shi & LaGanga, 2015). Capacity planning is even more critical in cancer clinics as patients benefit from early access to oncologists. However, there are few studies in the literature that address capacity allocation in oncology clinics. Saure, Patrick, Tyldesley and Puterman (2012) propose an MDP and its equivalent LP model to allocate patient demand to the available capacity such that costs of patient wait time and clinic overtime are minimized. Liu, Ma, Sauré, Weber, Puterman and Tyldesley (2019) present a methodological framework to improve capacity planning at an oncology clinic in British Columbia.

In most specialty care clinics, especially cancer clinics, patients have varying treatment requirements and follow complex care pathways. However, in almost all optimization studies in outpatient scheduling, either a single pathway for all patients or a predetermined pathway for each patient is considered, mainly because the treatment processes are highly unpredictable (Ahmadi-Javid et al., 2017). Therefore, uncertainties in patient care pathways have not received significant attention, and only a few studies (e.g., Rohleder, Lewkonia, Bischak, Duffy & Hendijani, 2011) take into account possible patient paths.

Simulation modeling has been extensively applied to address randomness and complexities in healthcare systems. Jacobson, Hall and Swisher (2006) provide an extensive review of applications of discrete event simulation modeling to healthcare systems. There are a number of studies in the literature that apply discrete event simulation in cancer clinics to allocate capacity to oncologists, schedule patients, reduce patient wait time, and increase resource utilization. For instance, Santibáñez, Chow, French, Puterman and Tyldesley (2009) apply simulation to analyze the simultaneous impact of resource allocation, scheduling, and operations on patient wait time, clinic overtime, and resource utilization in an ambulatory care unit in a large cancer center. Their objectives are different from this study as they focus on improving the patient experience by reducing patients' wait time after they arrive to the clinic and ultimately to reduce clinic overtime. Romero, Dellaert, van der Geer, Frunt, Jansen-Vullers and Krekels (2013) develop a simulation model to include variability in patient scheduling and measure the advantages of implementing a one-stop-shop for the treatment of skin cancer. Ma et al. (2016) use discrete event simulation to establish a scheduling framework for decision-makers at a cancer center. They show how to apply simulation to analyze the impact of oncologists' specialization configurations, the number of new patient consultation slots, and appointment scheduling rules on patient access. However, they do not consider returning patient demand in their study. Also, there are other studies (e.g., Liang, Turkcan, Ceyhan & Stuart, 2015; Woodall, Gosselin, Boswell, Murr & Denton, 2013) that use discrete event simulation to schedule chemotherapy and radiotherapy appointments in oncology clinics.

Patient no-shows and late cancellations are two environmental factors that complicate outpatient capacity planning. If patients cancel their appointments far enough in advance, the canceled appointment slots can be reused for scheduling other patients. Little research has been conducted to address this phenomenon (e.g., Schuetz & Kolisch, 2013; Liu, Ziya & Kulkarni, 2010; Parizi & Ghate, 2016). On the contrary, if patients cancel too late, appointment slots cannot be reused which is operationally the same as no-shows. Therefore, most studies that consider no-shows also include late cancellations.

In conclusion, although the literature in outpatient scheduling and capacity planning is rich, new patient access in oncology clinics has received limited attention. The few existing studies do not consider patient no-shows and cancellations, and to the best of our knowledge, no study addresses individual oncologist clinic flexibility and the idea of reserving slots for new patients.

3. Problem Description

Diagnosing cancer in the early stages and initiating treatment increases the chances of successful treatment outcomes. One of the key obstacles in the standard cancer treatment process is the delay in seeing an oncologist. Studies confirm that lack of resources and underutilized existing resources are the main reasons for the healthcare system's inability to deal with the growing number of new cancer cases (World Health Organization, 2020). Because oncologists are costly resources, cancer clinics try to highly utilize existing oncologists before considering hiring new oncologists. Efficient patient scheduling and capacity planning are very significant and impactful factors for improving providers' utilization. To ensure effective capacity planning, many uncertainties related to both resources and patients must be considered. This study proposes a simulation model to capture these uncertainties.

3.1. Simulation Model

This section describes the discrete event simulation model which is applied using data from an oncology clinic in Texas. Different clinic flexibility levels, specialization configurations, and operating strategies are designed and investigated. The performance of each scenario is compared based on new patient access defined as the average new patient wait time to see an oncologist.

Patients visit oncologists for three main reasons: 1) referral from a primary care physician (PCP) for cancer suspicion, second opinion, and consultation, 2) on-treatment visits, 3) follow-up visits. New patient referrals are received throughout the day and follow the process depicted in Figure 1 to be scheduled with an oncologist. Clinic observations indicate this process takes an average of 3 days to complete.

Figure 2 shows a representative patient flow used in the simulation model. After the first visit, oncologists create treatment plans for patients depending on the type and stage of cancer, possible side effects, and patients' preferences and overall health. Cancer treatment options available include: surgery, chemotherapy, radiation therapy, bone marrow transplant, hormone therapy, etc. Each treatment procedure includes several treatment visits and follow-up visits with oncologists. At any time during treatment, oncologists may decide to change the treatment plan due to ineffectiveness of the treatment or a patient's treatment reactions. Patients at the follow-up stage may start a new treatment plan due to cancer recurrence or metastasis, or may be moved to hospice. After completing the treatment plan and follow-up visits, cancer survivors are expected to return to the clinic every year for a few years.

Historical data and experts' opinions are used to determine different treatment regimens for different cancer types. There are 2 to 12 different treatment plans depending on the cancer type. Figure 3 shows an example treatment plan where patients complete eight treatment visits every two weeks and then follow two possible treatment paths. This example treatment plan shows that a vast majority of the patients (Path A) are treatable and finish the treatment visits (4-week visits), follow-up visits (3-month and 6-month visits), and move to survivorship, where they come back every year for five years. However, it is possible that the treatment changes (Paths B and C), or the cancer metastasizes and cannot be cured (Path D), and the patients begin hospice care.

The simulation model includes the following additional assumptions based on collected data and input from our cancer clinic collaborators:

- New patient demand remains unchanged over time.

- Providers' clinic days don't change over time.

- 25% of referrals request a specific provider, meaning 75% can be scheduled with any provider who is specialized in the patients' cancer type(s).

- Appointment durations are fixed: 40 minutes for new patients and 20 minutes for returning patients.

- There are different no-show rates for different cancer types. No-show rates for new patients vary between 4.3% to 21.3% (see Table 1 below) and are 5.7% for returning patients across all the cancer types.
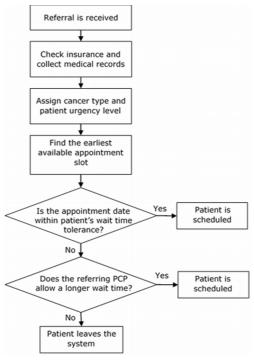

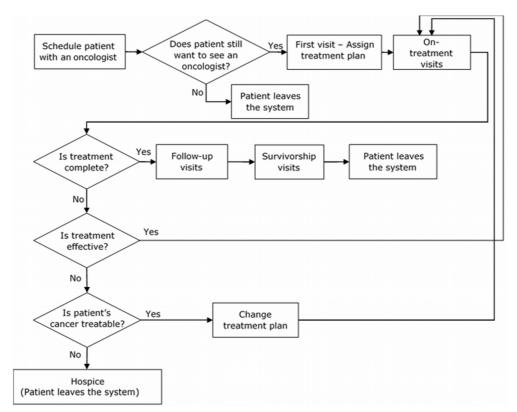Figure 1. New patient appointment scheduling process

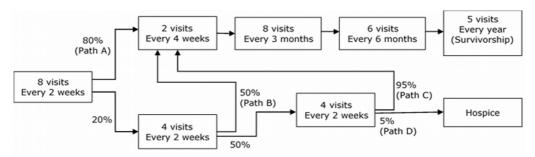Figure 2. Patient flow in the simulation model

Figure 3. A sample treatment plan

Cancer	No-show rate
Benign Hematology	0.213
Blood	0.133
Breast	0.043
Colon	0.050
Genitourinary	0.063
Head and Neck	0.120
Lung	0.154
Skin	0.000

Table 1. New patient no-show rates

- The appointment cancellation rate is 20% for new patients and 18.4% for returning patients. 50% of cancellations occur within two days of the scheduled appointment date (late cancellation), and some of the canceled appointments cannot be reused, which affects resource utilization and patient access.

- New patient appointments may be rescheduled up to three times due to cancellations or no-shows. However, returning patients generally follow their treatment plan and have at most one reschedule.

- All new and returning patients schedule their next appointment right after completing an appointment. Canceled and no-show appointments are rescheduled the same day patients cancel or miss their appointments, respectively.

- Patient and provider continuity of care is maintained unless a patient's cancer metastasizes to other parts of the body during treatment and the original oncologist refers the patient to another oncologist with the required specialization.

- The cancer center loses a percentage of its referrals for various reasons, including insurance denial and clinic-initiated canceling/rescheduling of appointments, which are never scheduled with an oncologist. There are also lost patients, meaning a new patient who is scheduled with an oncologist but never actually completes an appointment but may experience multiple no-shows or cancellations.

- Providers' days off work are considered, including holidays, vacations, conferences, etc.

- Current clinic practice lets individual oncologists address multiple cancer types (flexible clinics as defined in the next sections).

- New patients are scheduled in the first available slot of the appropriate oncologist.

Each simulation run has a combination of a clinic flexibility level and a specialization configuration which are explained below.

3.1.1. Specialization Configuration

Specialization configuration refers to the cancer types each oncologist is specialized in. Improving the specialization configuration to match capacity and demand for each cancer type is an important factor for responding to new patient demand in a timely manner. The oncologists in the cancer center under study see multiple cancer types ranging from two to eight types (see Table 2). Note that benign hematology is included in this table because these patients are seen by the oncologists and therefore contribute to the oncologist patient demand. For this reason, in the remainder of this paper when different cancer types are referenced, benign hematology is included. In this study, two specialization configurations are considered: the current configuration as given in Table 2, and a flexible specialization configuration where oncologists can see any cancer type, i.e., the restrictions in Table 2 are relaxed, and new patients can be scheduled with any of the oncologists.

Provider	Specialization mix
1	Benign Hematology, Blood, Breast, Colon, Genitourinary, Head and Neck, Lung, Skin
2	Benign Hematology, Blood
3	Benign Hematology, Blood, Colon
4	Breast, Colon
5	Benign Hematology, Genitourinary, Head and Neck, Lung, Skin

Table 2. Oncologists' current specialization mix

3.1.2. Clinic/Resource Flexibility

Some cancer types require that MDTs such as social workers, physical, occupational, speech, or recreational therapists, etc., be present to improve treatment quality and patients' overall experiences. Due to the significant cost of having MDTs, cancer centers desire to minimize the number of clinics that require the presence of MDTs by scheduling patients with the same cancer type on certain days of the week. For example, patients with head and neck cancer are often required to see dietitians and speech therapists after they visit an oncologist. The cost of the required supportive services can be reduced if patients with head and neck cancer can be seen on limited days of the week (for example, Tuesday mornings and Wednesday afternoons) instead of every day. Therefore, adjusting providers' clinic flexibility is one way to reduce the cost of MDTs. Clinic flexibility refers to how oncologists' clinics are allocated to each of the tumor sites they specialize in, i.e., the cancer types that oncologists see in each of their half-day clinics.

Three clinic types are considered in the simulation model depending on the flexibility in the number of cancer types assigned to each oncologist's clinic: fully-flexible clinics, semi-flexible clinics, and fully-dedicated clinics. These clinic types are explained below:

1. Fully-flexible clinics: oncologists can treat any patient of their cancer specializations in any of their weekly clinics. For example, provider 5 in Table 2 can see any new and returning patient with benign hematology, genitourinary, head and neck, lung, and skin cancer in any of his four weekly clinics shown in Table 3.

2. Semi-flexible clinics: each oncologist can only see two to three cancer types in each of his/her clinics. For instance, provider 5 in Table 2 can only see patients with benign hematology on Monday mornings, lung, skin, and genitourinary cancers on Tuesday mornings, head and neck and lung cancers on Wednesday afternoons, and benign hematology and lung cancers on Friday mornings. In semi-flexible clinics, cancer types within the specialization mix of providers are allocated to oncologists' half-day clinics based on new and returning patients' demands of each cancer type.

3. Fully-dedicated clinics: each oncologist's clinic is allocated to a specific cancer type, i.e., patients with particular cancer types are only seen on certain days. For example, patients with head and neck cancer can be scheduled with provider 5 on Tuesday mornings only. For the couple of providers whose number of

clinics and specializations do not match (for example, providers 1 and 5 in Table 2), clinics are designed similar to semi-flexible clinics. However, unlike semi-flexible clinics, those providers' clinics are divided into sub clinics, and a specific number of slots proportional to cancer demand are assigned to each sub clinic. For instance, a clinic with 12 slots may be divided into two sub clinics with assigned capacities of 5 and 7 slots, respectively, and each sub clinic is treated like a fully dedicated clinic. Similar to semi-flexible clinics, the capacity of each clinic and sub clinic is allocated based on the demand for each cancer type.

Provider	Clinics
1	Mon PM, Tue AM, Tue PM, Wed PM, Thu AM, Fri AM
2	Tue PM, Thu AM, Thu PM
3	Mon AM, Mon PM, Wed AM,
4	Tue PM, Wed AM, Thu PM
5	Mon AM, Tue AM, Wed PM, Fri AM

Table 3. Oncologists' weekly clinics

3.1.3. Reserve Slots for New Patients

The current practice in the cancer center under study is that new and returning patients can be scheduled in any available slot. In other words, new slots are not reserved for scheduling new patients. This can delay patient access, especially when cancer centers are short in capacity. The reason is that returning visits occur more frequently, varying from once a week to once a year depending on patient treatment status, and the visits are scheduled in advance. Therefore, returning visits consume a significant portion of the capacity, and if scheduling returning visits is not done properly, new patients have to wait longer. The cancer center data shows that 12.5% and 87.5% of the total demand belong to new patients and returning patients, respectively. This study explores the impact of four different policies for reserving slots for scheduling new patients. The first policy is to reserve the slots for scheduling new patients only. According to this policy, returning patients cannot be scheduled in new patient slots even if those slots ultimately remain unused. In the second policy, the slots are allowed to be used by returning patients if they were not utilized by new patients 1 day in advance, i.e., if an unused slot that was originally reserved for new patients is still available on the next day, the slot opens up for scheduling returning patients as well. The next two policies are the same as the second policy, except the reserved slots are open to schedule returning patients in 3 and 5 days, respectively.

3.2. Model Inputs

The simulation model inputs for new patient arrival rates are derived from two years of data that was collected for this study. Based on the data, the referrals (new patients) are classified into eight cancer types, including benign hematology, blood (malignant hematology), breast, colon, genitourinary, head and neck, lung, and skin. Table 4 shows the original referral rate for each cancer type. Moreover, since some of the referrals are lost (11.43% on average) without being scheduled due to insurance denials and other reasons, the effective referral rate for each cancer type is lower than the original referral rate. These values are presented in Table 4. Additionally, some patients in the effective referral rate never complete their first appointment (12% on average) but still consume slots due to multiple no-show and cancellation appointments where some of the slots cannot be reused. After accounting for lost referrals and reschedules for no-shows and cancellations, the total new patient appointment demand for each cancer type is shown in the appointment rate column in Table 4. A Chi-square goodness-of-fit test was performed to determine the distribution of new patients' referral rates. The test indicates that the daily referral arrival of new patients for each cancer type follows a Poisson distribution based on having all of the p-values > 0.05 (Table 5).

Based on experts' opinions, the new patient referral process, independent of cancer type, requires one to five days. Of the total referrals, 10% take 1 day, 20% take 2 days, 45% take 3 days, 20% take 4 days, and 5% take 5 days to be processed. Therefore, in the simulation model, a discrete random distribution with the aforementioned probabilities was used for assigning referral process times. Once the first appointment is completed, new patients become

returning patients and follow a treatment plan based on the given probability for each treatment path for each cancer type. As mentioned in Section 3.1, returning patients are scheduled for their next appointment right after completing an appointment. Therefore, returning patients reenter the system for completing or rescheduling their appointments based on the interval times between their visits. Patients ultimately exit the system due to completing their treatment plans, being moved to hospice, or death. Depending on the oncologists' full-time equivalence status for clinical duty, the number of clinics for each oncologist varies from 3 to 5 per week and the number of planned slots for each clinic varies between 7 and 12 slots.

Cancer type	Original Referral Rate (λ)	Effective Referral Rate	Appointment Rate
Benign Hematology	1.891	1.551	1.746
Blood	0.462	0.430	0.467
Breast	0.515	0.474	0.491
Colon	0.716	0.673	0.697
Genitourinary	0.160	0.154	0.161
Head and Neck	0.322	0.296	0.323
Lung	0.251	0.246	0.275
Skin	0.055	0.048	0.048

Table 4. New patient daily referral, effective, and appointment rates

Cancer type	Chi-Square	P-Value
Benign Hematology	4.257	0.513
Blood	1.914	0.384
Breast	2.058	0.357
Colon	1.534	0.675
Genitourinary	0.014	0.907
Head and Neck	2.565	0.109
Lung	0.543	0.461
Skin	0.182	0.670

Table 5. Chi-Square goodness-of-fit tests for new patient referrals

The system reaches steady state from the second half of year 8 of the simulation run. In other words, the average weekly numbers of new and returning patients in the system for two consecutive quarters becomes sufficiently close (less than a 0.40 patient difference for an average weekly total patient demand). In addition, the difference between the simulated average weekly total patient demand and the actual average weekly total patient demand is also very close (less than a 0.31 patient difference). The model is run for one more year, and the statistics from year 10 are collected for the experiments. The main reason for the long warm-up period is that there are many different treatment plans that are considered in the simulation model for each of the different cancer types. Depending on the cancer type, patients have a number of on-treatment visits, which take 3–12 months. Then, patients have follow-up visits, which take 2–3 years. After the follow-up visits, patients move to survivorship and return to the cancer center annually for 4–6 years. The vast majority of the patients (more than 99%) complete service in less than 9 years, and thus, it takes 8–9 years for the system to reach steady-state considering all of the visit types.

A pilot experiment was performed using 5 replications (n_0) to achieve an initial half-width (h_0). Then, the required number of replications to achieve a 95% confidence interval (h) was calculated using the following formula (Rossetti, 2015). The number of replications obtained was 18.3, which was rounded up to 20.

$$n = n_0 \frac{h_0^2}{h^2} \tag{1}$$

The simulation model was validated through statistical analysis of the clinic data and experts' opinions. The professional edition of the Simio Simulation Software was used for modeling the system because of its Application Programming Interface (API) capability, which allows us to extend the model in the future.

4. Results and Discussion

This section discusses the simulation results for implementing the policies introduced in Section 3 and comparing them with the clinic's current practice as defined in Section 3. Most of the current practices of the collaborating cancer center are held constant for the scenarios to better examine the individual impact of each policy change on new patient access. To keep utilization at reasonable levels, Sections 4.1 to 4.2 consider four levels of patient capacity ranging from 185 to 200. The current patient capacity in the observed clinic is 25 new and 150 returning patients. To investigate the impact of different scenarios on different capacity levels, the number of new patients is increased by 1 and returning patients by 4 for each increase of 5 in the patient capacity. Using this 4 to 1 ratio results in an integer linear increase in both the patient capacity and total slots and keeps the ratio of new patient capacity to returning patient capacity nearly the same across the different incremental increases in patient capacity. Table 6 shows the equivalent number of slots for each patient capacity as the two are not the same since new patients require two slots. Note that for larger values of weekly patient capacity the providers have to open additional clinics beyond the 19 clinics that they currently have.

Patient Capacity	Number of 20-minute slots
185	212 (27 new, 158 returning)
190	218 (28 new, 162 returning)
195	224 (29 new, 166 returning)
200	230 (30 new, 170 returning)

Table 6. Evaluated patient capacity levels

Note that in some of the experiments in this section that slot utilization is greater than 0.90. This can lead to work environments that are very demanding on clinic staff and are generally not recommended. Unfortunately, in our experience working with large government and private clinic settings, high utilization is commonly seen. No-shows provide some respite for medical staff. In addition, just because all slots are full does not mean all medical staff are continuously working. For example, one staff member may take the patient to a room and prepare the patient for a physician visit, but that staff member is not with the patient for the duration of the appointment. Similarly, a physician is typically with a patient less than 20 minutes for a 20-minute returning appointment. To know exactly how much work each healthcare worker is actually doing with each patient is an entirely different study which is worthy of doing but is beyond the scope of this research.

The steady-state statistics of the mean new patient wait time are measured by the number of workdays between the date a referral is received by the cancer center and the appointment date. If an appointment is rescheduled, the first scheduled appointment is used for the access metric. It should be mentioned that the half-width of the confidence intervals obtained for all the experimental results shown in this section are small and vary between 0.6% and 3.3% of the presented performance metrics. Therefore, only the mean value of the performance metrics is shown.

4.1. Resource Flexibility and Specialization Flexibility

To analyze the simultaneous impact of resource flexibility and specialization configuration on new patient access, the simulation model is run for six scenarios that are combinations of the two specialization flexibilities and three clinic flexibility levels explained in 3.1.1 and 3.1.2, respectively.

Figure 4 presents the results of these experiments. The simulation results highlight that new patients have the lowest wait time when clinics are fully flexible. Semi-flexible clinics perform almost as well as fully flexible clinics. This indicates that having moderate flexibility, which in practice is very implementable, is very beneficial. Moreover, a primary advantage of semi-flexible clinics is that the number of support staff could be reduced as MDTs for all cancer types are not required to be available on all days. It can also be seen that as the cancer center moves toward having fully dedicated clinics, patient access is more delayed. This can be explained by the fact that when clinics are dedicated and if new patients cannot be scheduled on the specific days of the week which are dedicated to their cancer type, they will have to wait longer to see an oncologist even though there might be available slots in other clinics of the providers on other days of that week. Therefore, although the MDT-related cost of operations is reduced when providers' clinics are fully dedicated, new patients will have to wait longer to see an oncologist.

As expected, the simulation results reveal that there is a correlation between specialization configuration and new patient access; the more flexible the oncologists are in the mix of patients they see, the lower the new patient wait time. The results also show that the impact of clinic flexibility on patient access is greater than specialty configuration. Since it is not practical to make major changes in the current clinic specialization configuration, a specialization mix analysis would be more applicable when hiring a new oncologist or if minor adjustments are made to the specialization capabilities of the oncologists to balance the expected workload across the providers.
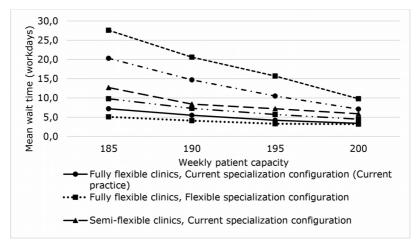

Figure 4. Effect of clinic flexibility and specialization configuration on patient access

4.2. Reserving Planned Slots for New Patients

According to the clinic template, 2-4 slots should be assigned to new patients in each clinic for individual providers. However, based on the collected data, the cancer center does not hold these slots for scheduling new patients and utilizes them for both new and returning patients. In this section, four scenarios for holding slots for new patients are considered and new patient access, reserved slot utilization, and deviation from treatment plans for on-treatment patients are evaluated for each scenario. The scenarios are presented in Table 7. To better understand the effect of holding planned slots for new patients, all other factors are held constant.

The simulation results for new patient mean wait time for the different scenarios are presented in Figure 5. The results confirm that scenario A, where slots are reserved for new patients, outperforms other scenarios in terms of new patient access. To further analyze the impacts of these scenarios, this study also looked into reserved slot utilization. The results suggest that although scenario A offers a low patient wait time, the slots are not efficiently utilized in this scenario (see Table 8). In fact, the slots are better utilized as clinics move from scenario A to scenario D because the reserved slots can be used for either rescheduling no-show and cancelled appointments or scheduling one-week follow-up visits. As mentioned in Section 3, half of the cancellations occur within 2 days of scheduled appointments. Therefore, the unutilized reserved slots in scenarios B and C can be used for rescheduling patients without affecting new patient access very much. In scenario D, the reserved slots can also be used for scheduling 1-week follow-up visits as the slots are released 5 days in advance.

Functional capacity planning in cancer centers must focus on reducing the lead time for new patients as well as guaranteeing the ensuing treatment plans for on-treatment patients as deviations from the treatment plan affect patients' health and effectiveness of their treatments. Therefore, to further study the impact of the proposed scenarios, this study also explores the deviation from the treatment plan for on-treatment patients under the different scenarios. For the purpose of this study, on-treatment patients are defined as patients with 1-week to two-month follow-up visits. Table 9 summarizes the results for treatment deviation for different weekly patient capacity levels. The results show that in scenario A when weekly patient capacity is 5.7% higher than the demand (weekly patient capacity of 185), about 44% of on-treatment patients deviate from their treatment plans by 5.2 workdays on average. The reason is that there is not enough capacity to schedule these patients on the prescribed days because a portion of the slots have been reserved for new patients and returning patients cannot be scheduled in those slots even though they are not utilized yet. This delay to see an oncologist is very crucial for on-treatment patients because oncologists need to evaluate patients' treatment progress to decide about future radiation therapy/chemotherapy sessions. However, in Scenarios B, C, and D, fewer patients deviate from their treatment plans as measured by a drop in the average days of deviation from the originally prescribed treatment plan.

The results confirm that at higher weekly patient capacity levels more patients can follow their prescribed treatment plans. In fact, fewer patients deviate from their prescribed treatment plans as weekly patient capacity increases to 8.6% greater than demand and more because the planned patient capacity for returning patients is better able to meet the demand. Overall, scenario D represents the best balance of providing good new patient access and slot utilization while minimally disrupting returning patients' prescribed treatment plans.

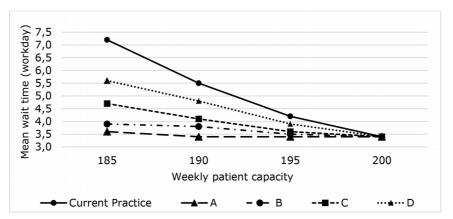| Scenario	Description
A	Reserve planned slots for scheduling new patients
B	Reserve planned slots and release them 1 day ahead if not utilized
C	Reserve planned slots and release them 3 days ahead if not utilized
D	Reserve planned slots and release them 5 days ahead if not utilized

Table 7. Scenarios investigated for holding planned slots for new patients

Figure 5. Effect of reserving new slots on patient access

Scenario \ Capacity	185	190	195	200
A	0.771	0.743	0.725	0.702
B	0.852	0.826	0.800	0.775
C	0.931	0.905	0.876	0.848
D	0.962	0.929	0.903	0.875

Table 8. Reserved slot utilization

Capacity	185		190		195		200	
Scenario	Patients deviated (%)	Avg. dev.	Patients deviated (%)	Avg. dev.	Patients deviated (%)	Avg. dev.	Patients deviated (%)	Avg. dev.
A	44%	5.2	23%	3.2	13%	2.6	7%	1.4
B	29%	3.6	16%	2.5	7%	1.5	3%	1.1
C	18%	2.7	8%	1.7	3%	1.2	1%	1.0
D	10%	1.8	5%	1.4	1%	1.0	0%	0.0

Table 9. Deviation from treatment plans for on-treatment patients

This research also investigated whether the clinic should hold the current number of slots for new patients and release them 5 days in advance (scenario D) or reduce the number of planned slots but hold them for scheduling new patients without releasing them (scenario A'). The number of planned slots was reduced by 10% in scenario A'. The results suggest that scenario D outperforms scenario A' because the new patient wait time is not significantly improved in scenario A' but planned slots are better utilized, and fewer returning patients deviate from their treatment plans in scenario D.

5. Conclusions

This paper presents a simulation model to assess different strategies to improve patient access in oncology clinics. The model utilizes two years of data collected from a cancer center in Texas. Several operating scenarios are considered, and their impacts on new patient wait time are investigated. Each scenario examined is a combination of several operational and tactical policies, such as clinic flexibility, specialization flexibility, and reserving slots for new patients. Four different weekly levels of patient capacity were evaluated, ranging from 185 to 200 by increasing weekly patient capacity in increments of five. It is clear from the experimental results that the overall provider utilization has to be kept below 95% in order to avoid new patients experiencing long wait times for appointments and that utilization values of approximately 90% or less are recommended. These recommendations correspond to having a weekly patient capacity of at least 185 but preferably 190 or more.

One of the main findings of this study indicates that clinic flexibility and specialization flexibility affect new patient wait time; however, the former has a more significant impact on patient access. New patient wait time reduces remarkably when provider's clinics are more flexible, and providers see any patient within their set of specializations in any of their clinics. Semi-flexible clinics perform almost as well as fully flexible clinics. This is valuable to know because semi-flexible clinics are more realistic to implement; after all, providers generally have limitations on the number of cancer types that they can see. Semi-flexible clinics are also less expensive to operate because MDTs are needed for fewer days than for fully flexible clinics.

This study further explores the effect of reserving planned slots for new patients and making them available a certain number of workdays in advance for scheduling returning patients. The results suggest that although reserving slots significantly improves new patient access, the treatment plans for some returning patients will be changed, creating potentially negative consequences if the capacity is not allocated properly to new and returning patients. The results suggest that if slots planned for new patients are released 5 days in advance to also be used for scheduling returning patients, more patients can follow their treatment paths and these slots are more efficiently utilized.

The current model does not consider the correlation between patient wait time and lost referrals. Research shows that the longer patients wait, the higher the probability they seek treatment elsewhere. Therefore, a future extension of the proposed simulation model is to correlate the lost referral rate with patient wait time because as the patient wait time is reduced, fewer referrals will be lost which in turn will increase the overall clinical workload.

Declaration of Conflicting Interests

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