Centralized Waiting List for Outpatient Physiotherapy in the Central Zone of the Nova Scotia Health Authority

by

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Abstract

This thesis utilizes discrete event simulation to model four outpatient physiotherapy locations in the Central Zone of the Nova Scotia Health Authority. Centralization of intake is being considered to increase efficiency and allow for pooling of resources in the network. The model allows the user to modify the scheduling policy, effectively changing the queuing discipline, to schedule patients in to New and Return appointments. Management is considering sending low priority patients to locations other than their origin hospital to alleviate their long and volatile wait times. The model also allows the user to modify the master schedule of available appointments, e.g. change the number of appointments or adjust the mix of New and Return appointments. The importance of the model is that management can quantify the impacts of scheduling decisions before making them.

List of Abbreviations Used

OA - Osteoarthritis

NSHA - Nova Scotia Health Authority

RPT - Nova Scotia Rehabilitation Centre

CPT - Cobequid Community Health Centre

VMPT - Veteran's Memorial Hospital

DPT - Dartmouth General Hospital

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Chapter 1: Introduction

Osteoarthritis (OA) is a condition affecting knees and hips that often leads to patients requiring total hip and knee replacement surgeries, known as arthroplasties. Physiotherapy is involved in the pre, peri and post-operative care in joint replacement. Physiotherapy has been shown to prevent disability and improve the quality of life in patients with OA of knee or hip (Fransen, McConnell, Hernandez-Molina, & Reichenbach, 2014). Referral models to physiotherapy, prioritization of patients, treatment modalities and outcomes measures lack standardization. There is a need for a better understanding of outpatient physiotherapy practices within the Nova Scotia Health Authority (NSHA), the organization of hospitals in Nova Scotia, Canada. Figure 1 shows a map of NSHA's coverage in Nova Scotia.

Figure 1: Map of the NSHA's coverage and management zones

There are eight outpatient physiotherapy clinics in the Central Zone of the Nova Scotia Health Authority. Four clinics have a significantly higher volume than the others and were chosen to be the subject of this research project. The four clinics are the Nova Scotia Rehabilitation Centre (RPT), the Veteran's Memorial Building (VMPT), the Cobequid Community Health Centre (CPT), and the Dartmouth General Hospital (DPT). These four locations are shown in Figure 2.

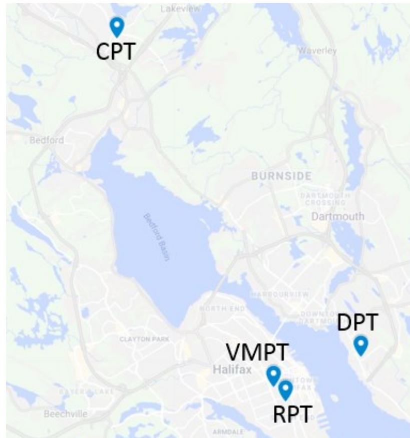

Figure 2: Locations RPT, CPT, VMPT and DPT shown on a map on Halifax

Each clinic operates its own referral, scheduling, and booking processes. Patients are referred to a clinic and may only join one wait list at a time. There are four categories of patients: Urgent, Priority 1, Priority 2, and General, each with their own target window to be seen within. Urgent patients face significant loss of function if physiotherapy is not provided within one week and should be seen within seven days. Priority 1 patients face a significant loss of function if their condition is left untreated for two weeks and therefore must be seen within 14 days. Priority 2 patients have conditions that would worsen if not seen within 2-4 weeks and therefore must be seen within 28 days. General patients require a physiotherapy intervention to optimize their function and should be seen within 56 days. Patients remain on the wait list until they are scheduled a first appointment. Once they receive their first appointment, they receive treatment through a series of follow-up appointments until they have completed treatment.

Generally, the network of clinics handle the Urgent and Priority 1 patients quite well. Patients usually have their first appointment within the target window. Like many other health services, the physiotherapy network of clinics struggles to accommodate the lower priority patients. They experience long wait times, in extreme cases waiting upwards of two years for their first appointment. The system is set up to cater to patients who have just undergone total knee and hip arthroplasties and while it accommodates these urgent patients swimmingly, it disproportionally underserves the low priority patients.

In addition to long wait times to first appointment for low priority patients, the network of four locations also struggles with variability in wait times. Some hospitals have extremely long wait times, while other hospitals experience almost no wait time at all. The access to outpatient physiotherapy in the Central Zone of the NSHA is inequitable because wait times for some geographic regions are much longer than others. Furthermore, patients of equal priority experience very different wait times depending on the hospital they are referred to.

The inequality in access to services is well known amongst NSHA outpatient physiotherapy management (hereby referred to as management), and decision makers. What is lesser known is the cause of the disparity in wait times. It is unknown whether the difference in wait times is due to inadequate allocation of resources, differences in clinical practices, differences in administrative practices, differences in patient populations or some other reason. What is known is that some locations likely have some extra capacity of resources because they rarely experience a wait time, while other locations seem to have no extra capacity and a high demand for resources, resulting in very long wait times.

NSHA management is interested in the idea of patients attending a different hospital than their original referral hospital if it would result in a shorter wait time. Effectively they are considering pooling resources by allowing patients to travel within the network of four locations. They are seeking to understand the benefit that could be gained by implementing this new scheduling policy. As presented in Table 1, the four locations are relatively close and it is believed that patients may be willing to travel within the network if it would result in a much shorter wait time.

Table 1: Total driving time without traffic between each of the four locations within the Central Zone

	RPT	VMPT	CPT	DPT
RPT		3 mins	23 mins	16 mins
VMPT	3 mins		21 mins	15 mins
CPT	23 mins	21 mins		19 mins
DPT	16 mins	15 mins	19 mins	

Management is specifically interested in low priority patients travelling to a different hospital, firstly because they are the population currently experiencing the longest wait time and secondly because they may have an easier time traveling to the appointment. Before implementing any new change in policy, management is seeking to understand the expected outcomes of their decision.

This research project was undertaken to explore and quantify the benefits that the Central Zone outpatient physiotherapy program can realize by pooling resources amongst locations by sending patients around the network of four locations, with the ultimate goal of reducing wait time for low priority patients and increasing fairness amongst patients of equal priority from different locations. Management believes that certain locations in the network have extra capacity and could help alleviate long wait times at other locations.

Chapter 2: Literature Review

Introduction and Accessibility

Outpatient physiotherapy is delivered in many Canadian hospitals serving patients with a variety of conditions, ranging from acute injuries to chronic conditions. The patient population utilizing public services usually does not have access to private care, typically because they do not have insurance and cannot afford the out-of-pocket cost. Physiotherapy and other outpatient rehabilitation services have been plagued with long wait times for many years. Murray and Berwick demonstrated that once a backlog on a wait list occurs, it can be very difficult to work through the backlog and return to a normal state (Murray & Berwick, 2003). Murray and Berwick, along with many others, describe the serious consequences for patients who experience long wait times for care (Murray & Berwick, 2003).

The primary objective of the Canada Health Act is to protect, promote, and restore the physical and mental well-being of residents of Canada and to facilitate reasonable access to health services without financial or other barriers (Government of Canada, 1984). Accessible healthcare is a vital component of a healthy population and society. While availability and quality of services are paramount, it is the accessibility of these services that determines whether citizens can utilize them. Gulliford et al. described accessible health care as meaning effective treatment for the entire patient population, with special consideration for the vulnerable (Gulliford, et al., 2002). Oliveria, in 2003, wrote that while public health care achieves one goal of accessibility in that services are free for patients, they often fail to provide equitable services across geographic regions (Oliveira M. , 2003). Mooney, in 1983, wrote about different meanings and interpretations of equity in healthcare in an attempt to reduce the confusion around different meanings of equity. He concluded that the meaning of equality of access to healthcare is only related to equal opportunity, and not about whether the opportunity to utilize the healthcare was exercised (Mooney, 1983).

Landry et al. reported that the burden of payment for rehabilitation services are shifting to the private sector (Landry, et al., 2006). Laliberé et al. cautioned that if this trend continues, vulnerable populations will not be able to access services due to their inability to pay the high costs of private care (Laliberté, Feldman, Williams-Jones, & Hunt, 2018).

Wait List and Prioritization Systems

Most, including Curtis et al, view prioritization systems in waitlist management as a fair way to allocate resources when demand exceeds supply (Curtis, et al., 2007). The association between queueing disciplines and resulting wait times has been reviewed in literature, including by Sobolev and Kuramoto who wrote that wait times depend on the queuing discipline or scheduling policies employed to sort the list of prioritized referrals (Sobolev & Kuramoto, 1974). In 2002, Swisher described how long wait lists disproportionally affected low priority patients and threaten equitability of priority systems (Swisher, 2002). In 2011, Foster at al described that in addition to patients' needs changing over time, potential benefits of treatment diminished with delayed care (Foster, Williams, Grove, Gamlin, & Salisbury, 2011).

Ni Shiothchain and Byrne wrote that when there are high volumes of high priority patients, low priority patients experience disproportionate wait times because the scheduling of their service can only begin after all higher priority patients have been scheduled (Ni Shiothchain & Byrne, 2009). Patrick and Puterman suggested that establishing maximum wait times for each priority level can help prevent endless waits for low priority patients (Patrick & Puterman, 2008).

In Australia, Brown and Pirotta sought to explore current prioritization practices and the evidence upon which they are based for physiotherapy community health services. They wrote that while the effects of prioritization practices on patients waiting for treatment are unknown, their existence demonstrates that decisions makers acknowledge that some patients' conditions may worsen while waiting (Brown & Pirotta, 2011). Brown and Pirotta present three approaches for ethically determining the order in which physiotherapy patients receive treatment: first come first served, level of clinical need, or level of ability to benefit. They argue that level of clinical need is the most ethical approach because it is difficult to determine a patient's ability to benefit from the service, and the first come first served approach would only suffice if all patients had equal need, as described by Purtilo (Purtilo, 1992). As described by Brown and Pirotta, Edwards concludes that the British Nation Health Service's policy of including time spent waiting as a priority criterion is politically motivated by desiring to reduce wait times (Edwards, 1999). Brown and Pirotta concluded that a lack of evidence supports current prioritization tools and that further research is needed in this area.

Briggs et al. published the results of a successful attempt to reduce wait times for urological surgery at Peninsula Health, a public health service in Victoria, Australia. They identified long surgery wait times as posing a serious risk for their clients (Briggs, et al., 2011). They implemented several measures to reduce these long wait lists and were successful. Similarly to other outpatient appointment systems, patients were given a priority and placed on the wait list accordingly, to ensure that high priority patients were seen soonest. Of the wait lists' 579 patients, 390 were overdue for their surgery, meaning they had surpassed the government-set standard. Their approach included the following: a wait list audit, improving communication between clinical and administrative staff, urgent caseload management, utilization of an Elective Surgery Access Scheme, hiring of an additional urologist, implementing a recall database, development of an outpatient service, and the creation of a day surgery initiative. Of particular interest is their approach to urgent caseload management. Briggs et al. reported that prior to the initiative, low priority patients were subject to extremely long wait times due to the difficulty in managing the urgent patients. The team tackled this problem by increasing capacity on an ad-hoc basis to keep on top of the urgent caseload. Clinics ran in to the evenings to accommodate urgent patients. Low priority patients benefitted from this change because urgent patients were seen promptly, rather than resulting in lower priority patients waiting for the backload of urgent patients to clear. This strategy and others resulted in the wait time for low priority patients (Categories 2 and 3) being reduced to 180 days from 248 days.

Lewis et al. conducted a systematic review of papers describing efforts to reduce wait times to first visits for community outpatient services. They studied musculoskeletal and cardiac rehabilitation services with the goal of identifying whether shorter wait times actually resulted in better health outcomes. They found low-level evidence that shorter wait times are associated with improved workplace participation for patients with musculoskeletal conditions, but inconsistent evidence that shorter wait times resulted in increased quality of life, patient satisfaction, and psychological symptoms (Lewis, Harding, Snowdon, & Taylor, 2018). Lewis et al. provided some other good conclusions, one being that the benefit of shorter wait times is most realized when the original wait time was very long. Further, they acknowledged that their research did not study the impact of waiting on patients while they are actually waiting. While it is true that it is possible that a patient's chronic disease may not progress significantly while they are waiting for care, meaning they will benefit from care in the same way whether they had waited one or two years, the time spent waiting was likely not time well spent. Finally, Lewis et al. wrote that long wait times may impact a patient's willingness to participate and attend appointments, adversely affecting their resulting outcomes.

Harding, Taylor and Leggat conducted a systematic review of literature related to the use of triage systems to determine how their use affected patient flow (Harding, Taylor, & Leggat, 2011). As described by Harding et al., triage systems are used by health systems and decision makers to ensure that the most acute patients are seen soonest. Harding et al. writes that little is known about the relationship between the use of triage systems and actual improvements in patient flow. Harding et al. reviewed 25 research papers to identify trends. Harding, Taylor and Leggat concluded that there is moderate level evidence to support that triage systems, when combined with some form of initial treatment, can have a positive impact on patient flow. They found conflicting evidence that using triage systems in the absence of any treatment improves patients flow. Finally, they concluded that, as expected, discharging patients at the time of triage can have a positive impact on wait times. It should be noted that the majority of the papers in Harding et al.'s study described triage systems in emergency department and is unknown whether their conclusions would apply to outpatient physiotherapy triage systems.

In 2016, Raymond, Demers, and Feldman studied waitlist management practices for home-care occupational therapy in Quebec, Canada. Similarly to previous researchers, they found that low priority clients waited disproportionately longer than higher priority clients, in some cases up to three years (Raymond, Demers, & Feldman, 2016). They suggested that these extreme cases threaten the Universality principle of the Canada Health Act. Of the 55 surveyed programs, 39 employed some strategy to address wait times for low priority patients, including formal policies such as maximum wait times, or informal efforts such as using clinical judgement to schedule a low priority patient over a high priority patient when deemed appropriate, or dedicating staff to low priority patients. Programs without wait list management strategies for low priority clients had larger wait lists and longer wait times. They argued that prioritization systems can be subjective, but that a patient's current time spent waiting is not, and therefore it should be considered when making decisions about the next client to service (Raymond, Demers, & Feldman, 2016).

Casas, Kenny and Barrett studied prioritization for elective dental procedures for children. They found that low priority cases made up the majority of the wait list and often were not accurately prioritized (Casas, Kenny, & Barrett, 2007). They implemented a new procedure for booking operating room time. While the new system was effective in reducing wait times for high priority patients, it disproportionately affected wait times for low priority patients.

Harding et al. explored the inevitability of wait lists in subacute ambulatory and community health services. Her research team conducted a qualitative analysis from the results of interviews of managers working in ambulatory and community mental health services, of which the largest proportion was physiotherapy. As described by Harding et al., ambulatory services receive less attention than more acute services, but patients still suffer from long wait times. They identified four themes in responses: intake and scheduling processes were inefficient, there was a lack of coverage for absent staff, there was a high demand for services, and staff had poor attitudes about wait times (Harding, et al., 2018). Of particular interest, participants reported that while the prioritization system worked well for high priority patients, low priority patients were never seen and their conditions just simply worsened. They also reported patients missing appointments as disrupting the clinic flow, as the appointments often went unfilled (Harding, et al., 2018). Finally, one participant noted that the nature of the service they provided was quite long term and that some patients never seemed to get better, reaching a chronic state of always requiring indefinite follow-up appointments. As described by Harding et al., adding additional resources is not always an effective solution to reducing wait times. Harding et al. wrote that wait times resulting solely from demand exceeding supply can be a misconception. One of Harding et al.'s conclusions was that the simplification of triaging, scheduling, and referral processes can lead to improvements in wait times.

As described by Gupta and Denton, it can be difficult to distinguish the difference between real wait time and patient-caused wait time because patients do not always accept the first available appointment. They may prefer to wait longer for care if there is a more convenient appointment time for them sometime in the future (Gupta & Denton, 2008). In 2013, Leung et al. studied the role patient choice played in influencing wait times for cataract surgery in Toronto. They found that 18% of patients declined the first available surgery date to find a better suiting one for their schedule (Leung, Vanek, Braga-Mele, Punch, & Ya-Ping, 2013). The median wait time for patients who declined the first available date was 8.5 weeks, compared to 6 weeks for those who did not. Educated, English speaking patients with strong support systems were more likely to decline the first available surgery and influence their wait time. Leung argued that because a large proportion of patients declined the first available surgery, it is possible that the unavailability of surgeons or facilities was not the largest predictor of wait time (Leung, Vanek, Braga-Mele, Punch, & Ya-Ping, 2013). This finding is relevant because it acknowledges that patient choice can affect wait times, and patients of different socio-economic groups choose differently. Leung concluded that decision makers should consider the role of patient choice when setting wait time guidelines.

Queueing Disciplines

In 1957, Kesten and Runnenberg defined the classical priority queuing discipline where a patient receives service only if all patients of higher priority have already received service (Kesten & Runnenburg, 1957). Low priority patients are repeatedly overtaken by higher priority patients and may never receive treatment, especially in systems with high volumes of high priority patients. In 1964, Kleinrock described a new discipline: the time-dependent priority queue, where patients move upwards on the waiting list at varying rates that are dependent on their priority and time spent waiting (Kleinrock, 1964). In 2014, Stanford, Taylor, and Ziedins proposed the Accumulating Priority Queue and used it to calculate the wait times for patients of varying Canadian Triage and Acuity Scale (CTAS) scores (Stanford, Taylor, & Ziedines, 2014). In 2014, Li and Stanford furthered their research by applying the Accumulating Priority Queue to a multi-priority, multi-server queue with heterogeneous servers. They derived the wait time for each type of patient according to First-Come-First Served, Classic Priority, and Accumulating Priority Queueing disciplines. Li and Stanford conclude that the Accumulating Priority Queue is an effective queueing discipline because it balances the advantages gained by the First-Come-First-Served and Classical Priority disciplines (Li & Stanford, 2016).

Drekic et al. created a model for deceased-donor transplant queue waiting times in 2013. They modeled a self-promoting priority queueing model, where a patient's priority could change over time as their condition deteriorated. Drekic et al. applied their model to liver transportation wait-list data from a regional health centre in Canada. Low priority patients waited in a separate queue than high priority patients but if their health deteriorated could be upgraded to high priority. Their model adequately predicted wait times for high priority patients, compared to empirical wait times (Drekic, Standord, Woolford, & McAlister, 2015). The model failed to accurately predict wait times for low priority patients.

Centralized Intake and Pooled Resources

Centralizing intake for outpatient services has been widely studied in literature. In accordance with the laws of queuing theory, centralizing intake can decrease wait times by better distributing demand around a network of capacity. Additionally, networks can reap the benefits of pooled resources. Finally, networks realize the benefits of standardized, streamlined, processes.

Wittmeier et al. studied the impact of centralizing intake for pediatric physiotherapy in Winnipeg, Manitoba. They found that centralizing the intake functions helped streamline processes and decrease wait times (Wittmeier, et al., 2016). Their study included a patient population with three priority levels. They concluded that centralizing intake improved equability in wait times and increased the quality of data collected about wait times.

Montecinos, Ouhimmou and Chauhan attempted to balance the loads in a network of Walk-in-Clinics (WiC) in Quebec, Canada by dispersing patients around the network according to their preferences and geographical locations. The patient knew the wait time for each WiC in the network before they made their decision. The model assumed that patients would leave their current WiC and go to another if they can be seen sooner, also accounting for travel time. Montecious, Ouhimmou and Chauhan utilized discrete event simulation to model their process and experienced an average patient gain of 112.7 minutes. Additionally, the workload in the clinics was more balanced (Montecinos, Ouhimmou, & Chauhan, 2017).

Yonek at al write that multi-hospital networks are now the most popular way that health organizations deliver services (Yonek, Hines, & Joshi, 2010). Mahar, Bretthauer and Salzarulo studied how multi-hospital networks can leverage the benefits of pooling (Mahar, Bretthauer, & Salzarulo, 2011). Mitropoulos cautions that while pooling demand for services can yield savings for the system, requiring patients to travel for their appointment limits the accessibility of the service, impacting its universality (Mitropoulos, Mitropoulos, Giannikos, & Sissouras, 2006). In their research, Mahar, Bretthauer and Salzarulo recognize that requiring patients to travel results in a cost for either the patient or health system. They formulate a cost function where the cost to travel varies depending on the priority of the patient. Further, they formulated an optimization model to study the cost of diverting patient demand around a network. They conclude that the cost of diverting a high priority patient to a different hospital is much higher than that associated with a low priority patient (Mahar, Bretthauer, & Salzarulo, 2011). The benefits of their optimal solution decrease proportionally to the patient population's level of priority: higher priority patients are more expensive to divert. Their results show that networks having hospitals in close proximity can especially realize the benefits of pooling (Mahar, Bretthauer, & Salzarulo, 2011).

Cattani and Schmidt examined how pooling customer demands and resources can lead to operational improvements. They used a warehousing example to describe how pooling can help companies deal with uncertainty in demand. By pooling the stock for two different geographical areas, higher demand in one area can be offset by lower demand in the other area (Cattani & Schmidt, 2005). Cattani and Schmidt identify the main benefits of pooling in queueing systems as being decreased wait times and increased utilization of servers. Further, they describe how there are diminishing returns in regards to the number of servers being pooled. The greatest improvement happens when two servers are pooled. Addition of a third resource to the pool yields benefits, but less benefit than the original result of pooling two servers. In other words, queueing systems stand to benefit from pooling of resources and can realize a great deal of that benefit even by pooling some of their resources.

In 2011, Sivey compared the effects of wait time and distance traveled for cataract patients. He utilized latent-class multinomial logit models to model the system and draw conclusions about the trade-offs between these two factors. Among other findings, he found that family physicians serving lower-income patient populations valued proximity of hospital less than those serving higher-income populations (Sivey, 2011). He also found that physicians serving older populations valued wait time more than those serving younger populations.

Outpatient Scheduling

Researchers have been studying how to improve hospital appointment scheduling for many years. In 1952, Bailey published early work on queues and appointment systems in hospital outpatient departments, with special reference to waiting times. Despite this research being published almost 70 years ago, his major findings are still relevant today. Bailey's work focused on the scheduling of patients into a clinic so to minimize patient waiting time as well maximize practitioner utilization time. Bailey provided an early description of the fundamental components of scheduling systems. He described the input process, meaning the appointment system that is used to schedule patients. Further, he describes the queue discipline, meaning the order in which patients are seen, and finally, the service mechanism, which he describes as the distribution of service times. This work is not concerned with service times as it is not focused on the schedule for a given day, but rather the schedule for a long scheduling horizon, ie months or years. Using random number charts and hand-drawn graphical comparisons, he compared various appointment systems and concluded that indeed the use of an appropriately chosen appointment system can reduce waiting times, improve utilization, and reduce the total number of patients waiting for an appointment in a waiting room (Bailey, 1952).

Klassen and Rohleder studied scheduling outpatient appointments in a dynamic environment. Their focus was scheduling patients in for an appointment as they call, without knowing who will call later in the day, thus creating a dynamic environment. They compared several scheduling rules and measured how each performed in terms of wait time and provider utilization. Klassen and Rohleder used simulation to compare 30 different combinations of scheduling rules, number of urgent appointment slots, expected service times, and expected variation in service times. Their research goal was to determine what scheduling rule had the greatest impact on scheduling under a variety of conditions. Their research was focused on how to schedule clients in to a clinic so to minimize wait time on that day. They found that clients with low expected variance in service times should be scheduled earlier in the day, while variable clients should be scheduled later in the day (Klassen & Rohleder, 1995). Further, urgent appointment slots should be scheduled later in the day, to allow more time for them to be filled, although doing this negatively impacts wait time.

Simulation

In 2010, Gunal and Pidd reviewed uses of discrete event simulation in the hospital setting. They concluded that discrete event simulation has been a widely used approach for several years, most models focus on a very specific problem, and few have created generic models (Gunal & Pidd, 2019).

In 2012, Bowers, Ghattas, and Mould utilized simulation to study an orthopaedic outpatient clinic. They worked very closely with clinical staff and involved them throughout all stages of modeling, including training them how to use the model. They reported that this approach resulted in the clinical staff being very confident and engaged in the model (Bowers, Ghattas, & Mould, 2012). Brown et al. categorized the benefits of discrete event simulation in healthcare in to two categories: hard and soft. As described by Brown, a hard benefit of discrete event simulation is its ability to determine the balance of resources required to meet a certain standard, while serving a varying demand (Brown & Pirotta, 2011). Brown et al. also described the softer benefits of simulation, which include the benefits gained from organizing data to be used for simulation, even if the simulation is never completed. Another soft benefit of simulation is that the process of designing the model allows clients to understand the role of their service and processes within the larger healthcare system (Brown & Pirotta, 2011). The findings of discrete event simulation can be very helpful for decision makers and schedulers as they allow for analysis of outcomes before a decision is made. Brown et al. advocated for researchers to train clinical staff on how to use simulation models so that they can easily predict the outcomes of decisions such as modifying resource levels. They argue that doing this improves the simulation's sustainability and potential for reuse.

Banks et al. described simulation as a tool used to model a real or hypothetical situation so that a researcher can learn about the system (Banks, Carson, Nelson, & Nicol, 2001). Ortiz-Barrios et al. concluded that simulation is a very powerful tool because it allows researchers and decision makers to evaluate options or policies before actually implementing them. Ortiz-Barrios utilized discrete event simulation to model an integrated outpatient internal medicine network between two hospitals to evaluate the project wait times and resource utilization. They argued that a key factor in successful network scheduling systems is effective communication between hospitals (Ortiz, Escorcia-Caballero, Sanchez-Sanchez, Felice, & Petrille, 2017). The processes must be supported by information systems that enable schedulers to understand the current capacity of each hospital and allow them to schedule the patient for the earlier available appointment in the network. In their proposed model, the scheduler assigns the patient the earliest appointment, which could either be at their origin hospital or the other hospital in the network. The model had varied results, with one hospital experiencing a 150% reduction in lead time, and the other hospital experiencing a 75% increase in lead time (Ortiz, Escorcia-Caballero, Sanchez-Sanchez, Felice, & Petrille, 2017). The results are somewhat limited because the network only contained two hospitals.

Brailsford conducted a review of literature in operations research in healthcare and found simulation to be the second most common method, after statistical analysis (Brailsford, Harper, & Patel, 2009). Lent, VanBerkel, and Harten reviewed the relationship between simulation and actual measured improvements in hospitals. As summarized by Lent et al., at least seven reviews of the use of simulation in healthcare have already been conducted. Previously, VanBerkel and Blake concluded that simulation should be regarded as a mature tool within operations research (VanBerkel & Blake, 2007). After reviewing the relevant literature, van Lent et al. reported that while simulation in healthcare is a widely studied topic, few have actually measured the impact of implementing recommendations from simulation models (ven Lent, VanBerkel, & van Harten, 2012). They conducted a survey of researchers and a review of literature to analyze how often simulation recommendations were actually implemented, what factors contribute to whether the recommendations were implemented, the methods used to evaluate implemented recommendations, and the discrepancies between what was written about in literature versus what was actually implemented. They identified and ranked the factors related to the technical qualities of simulation studies and found data availability, validation and verification through historic data, and quality of the conceptual model to be the three most important. Regarding process quality, they found client commitment and appropriate use of animation to be the most related. van Lent et al. conclude that while researchers reported implementation of results in 44% of studies, the literature shows an implementation rate of 18%. Furthermore, there is very little evidence of actual improvements related to these implementations (ven Lent, VanBerkel, & van Harten, 2012). Finally, van Lent et al. found that only 8 of the 89 studied papers reported having implemented the recommendations in more than one setting. They propose that because modelers must work so closely with one single client, the resulting simulation may not be appropriate for implementation in other jurisdictions (ven Lent, VanBerkel, & van Harten, 2012).

As described by Gupta and Denton, timely access to care results in positive outcomes for patients. Scheduling systems can act as gate keepers to care, especially for patients disproportionally disadvantaged by the scheduling rules (Gupta & Denton, 2008). Gupta and Denton describe the allocation of physical resources and staff as well as prioritization rules and scheduling systems as the key factors impacting timely access to care. They describe one of the benefits of having superior scheduling systems as allowing health systems to vary their supply to match their demand, all while balancing patient and provider preferences. Gupta and Denton focused on access rules, encounter start times and approaches for handling differences in supply and demand on a daily basis. Of particular interest is their work on access rules, which they define as including how patients are prioritized, along with how much capacity is reserved for each priority.

Gupta and Denton cite patient preferences as being a barrier to implementing optimal scheduling policies. Gupta and Denton attribute the fact that most patient scheduling systems require an actual human scheduler, rather than an automated system, to patient preference. Patients will prefer a convenient time rather than the most optimal appointment time, obviously to no fault of their own. IT systems capture the referral and appointment dates, generating the elapsed waiting time, but most do not track the more qualitative information about the booking process, ie which options were made available to the patient and whether the patient chose the soonest appointment or another one.

Optimization

Rezaeiahari and Khasawneh developed an optimization model for scheduling patients in destination medical centers, targeting medical tourists. Their model had two goals: to minimize the difference between a patient's preferred start time and their actual start time, and to minimize the time between procedures for patients with multiple procedures. Previously the Mayo Clinic in Rochester, NY utilized compact scheduling to benefit patients who could not travel and return multiple times for multiple appointments, and who would benefit from having their appointments close together. Rezaeiahair and Khasawneh felt that most previous studies had focused on creating optimal schedules for patients with one single appointment. They declared their research unique because it focused on inter-waiting time between procedures. They developed a hybrid algorithm combining a mining heuristic and a local search method to solve their optimization problem to determine the near-optimal scheduling method for minimizing inter-appointment wait time (Rezaeiahari & Khasawneh, 2017).

Appointment Attendance

Gupta and Denton cite uncertainty in demand, patient and provider preferences, and cancelations and no-shows as contributing factors to schedulers' inability to balance supply and demand (Gupta & Denton, 2008). No-shows and cancelations are particularly impactful for clinics with reduced supply or where their rates are very high, wrote Gupta and Denton. Mbada et al. studied the impact of missed appointments for outpatient physiotherapy in terms of cost, efficiency, and patients' recovery. Their focus was an outpatient physiotherapy clinic in Nigeria with a severe missed appointment rate. They found that 79.2% of appointments were missed. As described by Mbada et al., missed appointments disrupt clinic flow, and result in underutilization of resources. Unsurprisingly, this extreme missed appointment rate significantly impacted recovery time for patients and was costly for the clinic (Mdaba, et al., 2012).

Gupta and Denton provide common barriers faced by patients who do not show up for their appointment: lack of transportation, day-care, or being unable to take paid time off work. Lacy et al. conducted a survey of patients who missed appointments. As described by Lacy et al., the most reported reasons for no-shows were fear of discomfort during the appointment, patients perceiving that the healthcare system disrespects their time, or patients believing that the time previously reserved for their missed appointment can be used for something else productive if they miss it (Lacy, Paulman, Reuter, & Lovejoy, 2007). LaGanga and Lawrence used the results from their simulation to demonstrate that overbooking patients, in anticipation that some will not show up, can improve flow without impacting wait times (LaGange & Lawrence, 2007).

Wait List Management Strategies for Physiotherapy

In 2010, Passalent explored prioritization and wait list management strategies in publicly funded physiotherapy and occupational therapy in Ontario. She identified 14 different strategies in place to manage wait lists. The most common strategies were encouraging patients to self-manage their injury and implementing attendance policies (Passalent, 2010). The least common strategies were centralizing the wait list and introducing a maximum wait time. One respondent reported that their outpatient physiotherapy clinic resorted to eliminating services for low acuity referrals, only accepting high acuity and specialty patients. Their resources were so limited that they could not see those patients in a reasonable time frame, and therefore decided not to accept them to their wait list at all. Passalent reported that the use of centralized wait lists was not common, despite the Auditor General of Ontario recommending it in 2004. In a previous paper, Pattison described the use of centralizing physiotherapy wait lists as reducing the wait time from 16 weeks to four weeks (Pattinson, 2003).

In 2001, Rastall and Fashanu conducted a survey to organizing information about the extent and management of outpatient physiotherapy waitlists. They surveyed 54 outpatient physiotherapy departments in the United Kingdom. Of these departments, there was only one that did not utilize a priority system in its waitlist (Rastall & Fashanu, 2001). The results of the survey showed that acute/urgent patients were being seen ahead of target, sub-acute patients were being seen on target, and chronic/routine patients were being seen on average five to six weeks after their initial target of five weeks. Rastall and Fashanu gathered information about wait list management strategies for departments self-identifying as having a wait list problem. From most to least effective, the strategies included the following: Improve Appointment System and Reduction of Non-Attendance, Caseload Management, Staffing Arrangements, Communication with Doctors, and Patient Management. The most frequent Caseload Management method was to ensure that a certain number of new patients are seen per week, for example by dedicating a staff member to seeing new or low priority patients. Rastall and Fashanu concluded that low priority patients experienced disproportionate wait times and that some wait list management strategies were effective.

Laliberté at al studied wait list management strategies for three hospital outpatient physiotherapy departments in Montreal. They reported that increasing wait lists were causing ethical concerns for staff and frustrations for patients (Laliberte, Feldman, Williams-Jones, & Hunt, 2018). They conducted a survey of clinicians to study how they made prioritization decisions and strategies that they employed to manage their waitlists. One strategy was to reduce appointment frequency; another was to limit access to services for patients that had previously accessed the service for the same injury. Some clinicians reported having separate wait lists for certain types of patients; i.e. patients referred from the emergency department or pain clinic. The study unearthed another unique practice: hospital employees had their own wait list. Some reported that this resulted in efficiency gains by allowing schedules to fill cancelled appointments with nearby hospital employees. Others identified a lack of fairness with this approach, as employees had health insurance and could have access to private care. Another strategy was to redirect patients having insurance to private clinics. Strategies specific to low priority patients included the use of group classes and home programs, which were effective for patients with chronic conditions. Another strategy was to dedicate one physiotherapist to low priority patients. One drastic strategy was proposed: some clinicians felt that they should entirely restrict access to care for low priority patients. They felt they were creating false hope for low priority patients who might never actually receive service and concluded that they should at least be as honest as possible about their wait time. Clinicians raised the issue that elderly, chronic patients deemed low-priority would disproportionally suffer from long wait times, diminishing the equity of the service (Laliberte, Feldman, Williams-Jones, & Hunt, 2018). Finally, clinicians reported that patients who experienced long wait times had higher expectations for treatment.

Harding and Bottrell attempted to improve outpatient physiotherapy wait times by implementing an appointment system called Specific Timely Appointments for Triage (STAT). The STAT model requires clinicians to dedicate a certain amount of time in their schedule to triaging and assessing new patients. Clinicians are encouraged to consider the current demand for their service and therefore make triage decisions based on the current wait times for each priority. The study was successful and patients experienced an improvement from 18 to 14 days for time from referral to first appointment (Harding, et al., 2018). Additionally, the total number of appointments was reduced. Harding and Bottrell suggest that the STAT model may have prevented long wait lists forming for low priority patients while still accommodating high priority patients by allowing clinicians to make decisions about priority in response to the current demand. The model achieves equity in one sense by giving more acute low priority patients a chance to be deemed higher priority if the low priority wait list is very long, but fails to achieve equity in that two patients presenting with identical conditions but at different times may be given different priorities.

Deslauriers et al. studied various waiting list and management strategies for publicly funded outpatient physiotherapy services. They felt that the association between wait list management strategies and reduced waiting times was not well understood, and therefore sought out to determine it (Deslauriers, et al., 2017).

As described by Deslauriers et al., early intervention for physiotherapy patients is associated with reduced pain and psychological symptoms. Deslauriers et al. describe how patients who can afford private physiotherapy care will seek it over facing long wait times for publicly funded care. Unfortunately, patients who cannot afford private care are disproportionally affected: wait times are long in public physiotherapy, and patients who cannot afford private care are more likely to be the ones requiring physiotherapy in the first place (Deslauriers, et al., 2017). As described by Gibson et al., this problem poses ethical concerns (Gibson, Martin, & Singer, 2005).

They conducted a survey of 97 outpatient physiotherapy services in Quebec. Only five of the 97 clinics utilized a centralized waiting list, ie pooled resources with other locations. 95 of the 97 hospitals had a wait list and the mean waiting time was greater than 6 months for 41% of locations. The three most frequently used wait list management strategies were prioritization systems, attendance policies, and redirection of patients to another service (Deslauriers, et al., 2017). Other reported strategies with evidence of success were maximum wait time targets, group interventions, and discharge criteria. Strategies that were not associated with shorter wait times included maximum number of appointments per patient and mandatory caseload for clinicians. Their conclusion was that the most effective strategy to increase access for services was to conduct an initial evaluation to prioritize patients and then organize the waitlist accordingly (Deslauriers, et al., 2017). Deslauriers et al. proposed some other interesting ideas regarding physiotherapy wait lists, one being that physicians who know about the long wait lists may be reluctant to refer their patients, resulting in the number of patients waiting being an underestimation of the true demand. Further, they identified that wait times for patients that actually received services were much lower than for patients still waiting. This is because for 62.9% of respondents, lower priority patients could not receive services before a higher priority patient, even if they had been waiting for far too long (Deslauriers, et al., 2017). The reported wait time only included patients that actually received services. Caution should be taken in examining wait times for systems with prioritization: lower priority patients wait much longer and are disproportionally affected.

Discussion

The use of triage systems in healthcare services with limited resources is necessary to effectively ration care and ensure that patients with urgent needs are served in a timely fashion. While these triage systems generally serve urgent patients well, low priority patients are often disproportionally disadvantaged. Many triage systems only allow low priority patients to be seen if no priority patients is waiting ahead of them, sometimes leading to extremely long wait times for low priority patients.

Much of the research in hospital outpatient appointment scheduling to date has been focused on how to organize appointment starts times within a clinic to minimize how long a patient waits to see a clinician and to maximize the clinician's utilization. In contrast, the goal of this research is to improve wait times for low priority patients and to increase fairness amongst patients from different areas.

Gupta and Denton argue that the application of industrial engineering and operations research techniques and models could majorly impact appointment scheduling in healthcare. While other industries have already fully embraced these techniques, Gupta and Denton believe there is still great room for improvement in healthcare. Their main argument is that because decision makers in healthcare often lack analytical or technical background, they are resistant to solutions produced from these fields (Gupta & Denton, 2008).

Outpatients appointment scheduling has been widely studied and numerous researchers have made significant contributions, both in simulation and optimization. Centralized queues and the pooling of resources can lead to great improvements in patient flow. There has been a lack of published work relating to how the use of simulation can improve access for low priority patients. This research project will use discrete event simulation to explore different scheduling strategies in an attempt to reduce wait times for low priority patients. To the best of our knowledge, previous researchers have not modeled multiple patient type scheduling in an outpatient network with partial pooling for a real-world problem using real historical data.

Chapter 3: Descriptive Statistics

The data for this project was generated from a custom report prepared by a data analyst, who merged registration data and appointment data from STAR, the hospital's registration system, and PHS, the physiotherapy department's scheduling system. The record level data included a history of all appointment types and statuses including those that were cancelled, either in advance or at the last minute (no-shows). The report also contained patients who were still waiting for an appointment. Every row of data, representing a patient's most recent interaction with the two systems, contained a referral date. The raw data contained all of the necessary information required to understand a patient's outpatient physiotherapy journey including when they were initially referred, how they were prioritized, how long they waited for their first appointment, how often they were seen for follow-up treatment, and when their follow-up treatment ended. This chapter details all the steps of the data analysis which was completed to understand the patient demographics, scheduling practices, wait times, and treatment lengths.

Appointment Statuses

There are five unique appointment statuses within PHS, reflecting the different ways that a patient's interaction with the system can be recorded: Arrive, Cancel, No-Show, Schedule, Wait.

Appointment Status	Description
Arrive	A patient arrives for and receives their scheduled appointment
Schedule	A patient is scheduled for a service
No-show	A patient fails to arrive to their scheduled appointment
Cancelled	A patient cancels their appointment
Wait	A patient joins the wait list for an appointment

Figure 3: PHS Appointment statuses and descriptions

Time Period

The raw data set included 80029 patient interactions with the PHS and STAR systems. This study includes data from January 1st, 2017 to September 28th, 2018. It was decided that a dataset representing a period of 20 months was sufficient for the needs of this model. Records captured prior to this period were omitted for a few reasons. Patients that were referred prior to 2017 may not have had their referral date captured because data collection processes were different at that time. Further, clinical practices have evolved over the years. The model should reflect the current clinical practices regarding how often and for how long patients are seen, in addition to the current scheduling practices.

Referral Analysis

Each PHS record includes a patient's referral date. The arrival rate, meaning the rate at which new referrals joined the wait list, was generated by collecting and organizing each unique patient's referral date. The empirical arrival distribution was generated from this ordered referral list. Referrals were analyzed separately for all four locations. Figure 4 shows the empirical distribution of inter-arrival time, measured in days, for all four locations:

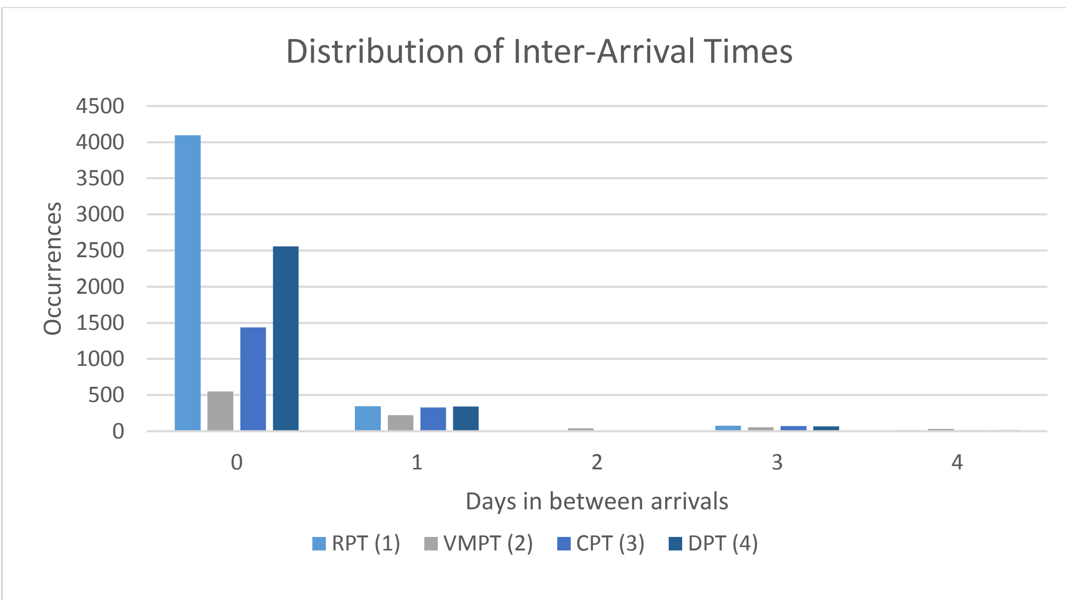

Figure 4: Distribution of inter-arrival times for all four locations

In addition to understanding how often patients joined the wait list, it was important to understand the mix of each four priorities. There are four priority types: Urgent, Priority 1, Priority 2, and General. Figure 5 shows the mix of each priority arriving at each location. The Veteran's Memorial Building (VMPT) has historically handled the vast majority of the post-surgical arthroplasty patients on peninsular Halifax, explaining its high portion of Urgent patients and the RPT's low portion of Urgent patients. It should be noted that all four locations have the practical capability to handle all priority types.

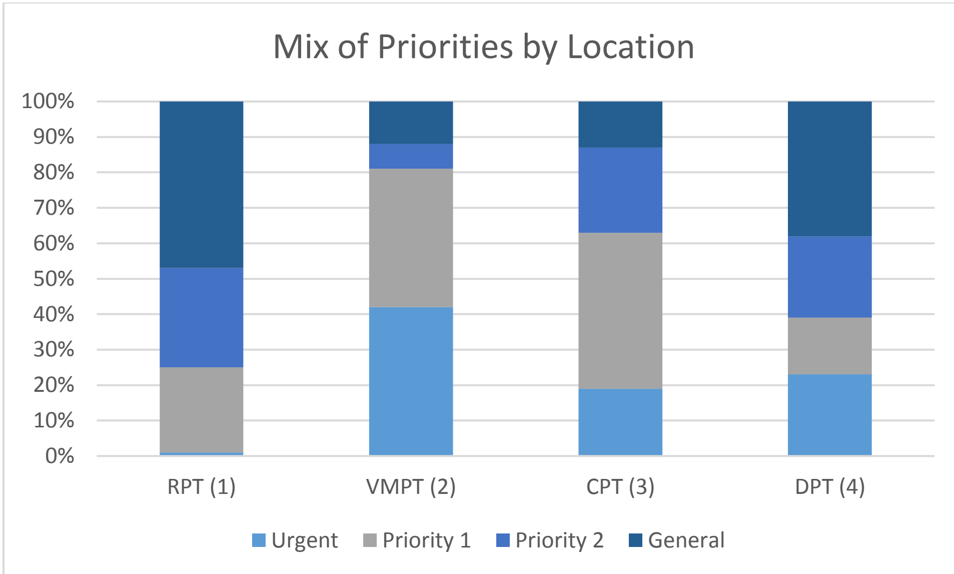

Figure 5: Mix of Urgent, Priority 1, Priority 2, and General patients for each location

Wait Times

The wait time of concern for management is the wait time to first appointment, i.e. the time a patient must wait before entering a physiotherapist's caseload. The wait times were computed from the data by identifying each patient's first appointment date and comparing it with their referral date. The wait times were calculated for each priority at each location. The resulting historical wait times to first appointment, for all 16 types of patients, are presented in Figure 6. High priority patients wait less than lower priority patients in every location, suggesting that the use of priority system is effective, or at least exists. CPT and DPT have long wait times and their lowest priority patients wait exceptionally long. The most striking information about the wait times is that they are very variable for low priority patients. General patients at the RPT and VMPT wait, on average, less than 20 days for this first appointment.

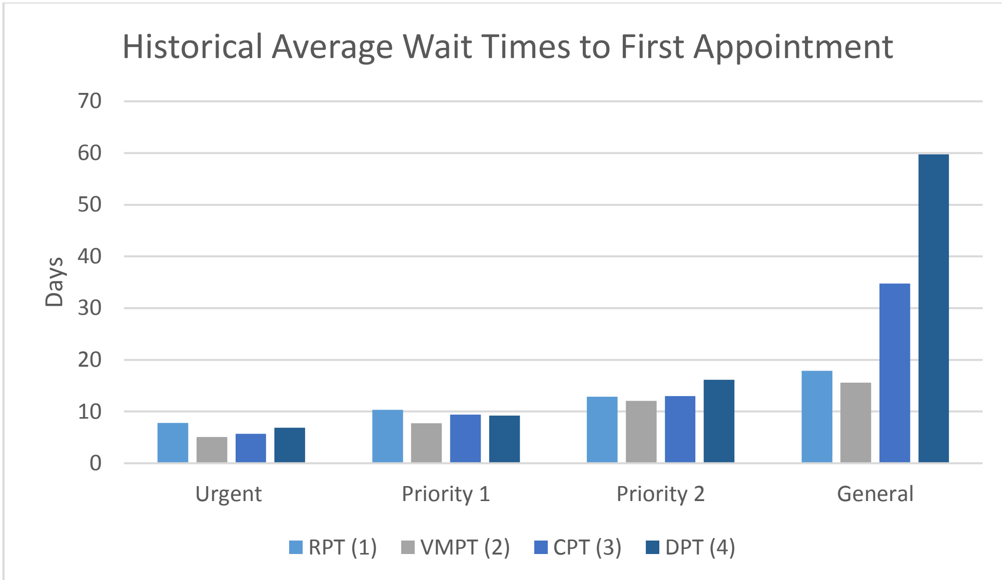

Figure 6: Historical wait times to first appointment for all priorities and locations

The average General patient at Dartmouth waits 60 days for their first appointment, with some wait times approaching 100 days or more. Figure 7 shows the historical wait time to first appointment for General patients at DPT over during the same time frame as the data for this project. The wait times are very volatile.

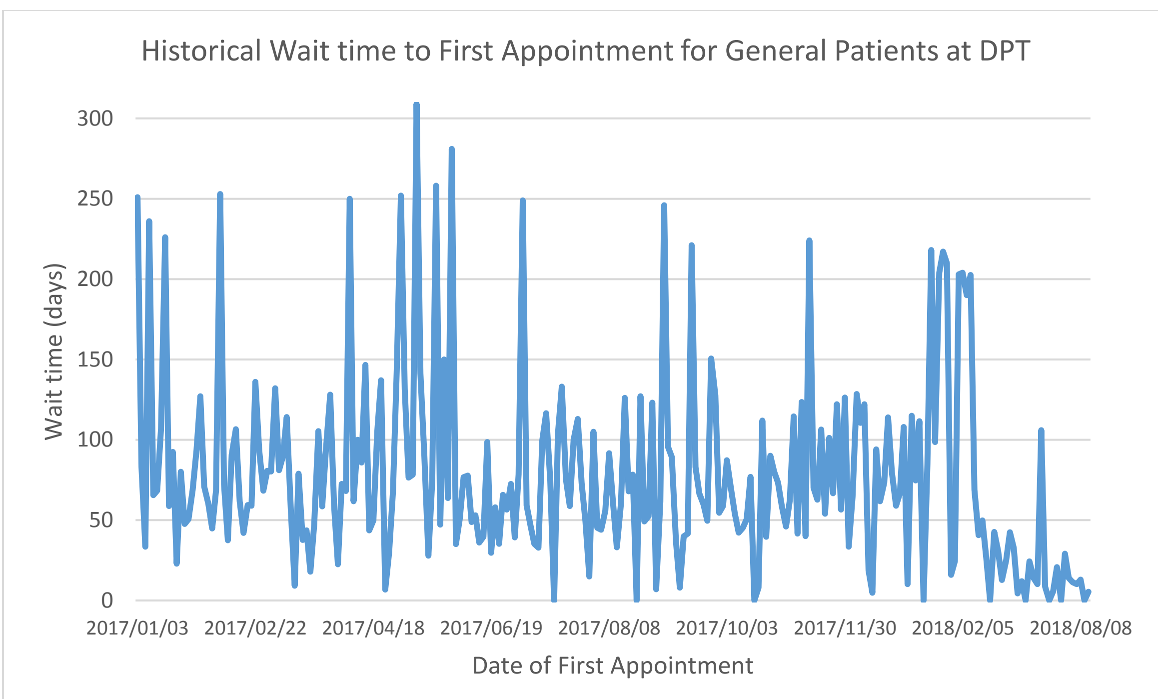

Figure 7: Historical wait time to first appointment for General patients at DPT

While they seem to have decreased in the 5 months at the end of the period, we have no information about whether more resources were added or if any other measures were taken to try and decrease wait times. The only conclusion that can be made about historical times is that they are long and volatile.

Return Appointments

A secondary objective of this work was to understand clinical practices regarding follow-up appointments. Management believes that wait times to first appointment could be reduced by adjusting the appointment mix to include more new appointments and less return appointments. The following two data elements regarding follow-up appointments were analyzed:

- Time in between return appointments
- Mean number of return appointments

The time in between appointments and mean number of appointments were calculated by analyzing historical records of appointments where the appointment status was Arrive and patients showed up and attended their appointment. The results of this analysis are presented in Table 2. The results are as predicted by management, some clinics see patients much more often than others. Management believed this was the case but previously could not quantify it.

Table 2: Average number of return appointments and days in between return appointments

Location	Priority	Average # of Return Appointments	Average # of Days in between Return Appointments
RPT (1)	Urgent	7	9
	Priority 1	7	9
	Priority 2	6	9
	General	5	11
VMPT (2)	Urgent	12	6
	Priority 1	8	8
	Priority 2	5	8
	General	2	11
CPT (3)	Urgent	8	6
	Priority 1	8	8
	Priority 2	5	12
	General	6	7
DPT (4)	Urgent	7	8
	Priority 1	5	10
	Priority 2	3	12
	General	3	13

Bookable Appointments

Information about the number and type of bookable appointments for each location was not readily available. The scheduling process involves retrieving the master schedule in PHS, finding a free slot of the correct type meaning New or Return, and scheduling the patient into the slot. Each location had different practices regarding documentation and time between appointments. Some locations reserved time for documentation while clinicians in other locations completed documentation during the patient visit or at some other time. A need was identified to use a standardized approach to estimate the number of bookable New and Return appointments due to the lack of standardized information available.

The starting point for this analysis was the master clinician schedules for each location. These master schedule were obtained in a variety of means, ranging from screenshots of PHS, to Word Documents, to verbal explanations of availability. This master schedule represents the upper limit of bookable appointments, meaning if everybody worked every day, spent their full day with patients, and used every single appointment. There are many factors affecting appointments that lead to fewer appointments actually being available than this upper limit. Some include: holidays, employees away from work for planned reasons (e.g. vacation), and employees away from work for unplanned reasons (e.g. snow storms and sick time). It is the opinion of managers of the clinics that the schedule is not fully utilized, meaning that appointments go unfilled or the scheduling is generally not efficient. Finally, some clinics do not have a wait list and therefore would not always operate at full capacity. This would also lead to unfilled appointments. Table 3 shows the capacity analysis to estimate the number of bookable appointments of each type for all locations. It is assumed that there are 12 holidays a year, physiotherapists have three weeks of vacation, and spend 5% of their time away from work due to unforeseen circumstances such as being sick, attending a medical appointment, or a storm day. The right-most column is the weekly number of each type of appointments that are actually available to be booked. Of the total 1503 weekly appointments in the master schedule, it is expected that only 1272, or 85%, of these appointments are actually available to be booked. 85% is a conservative bookable appointment rate that will be re-examined later in this paper. It is considered conservative because the assumptions of employees only having three weeks vacation and only being away from work 5% of the time are conservative. Further, many appointments will be lost due to employees spending time on activities other than patient appointments.

Table 3: Analysis of bookable appointments

Day	Location	New or Return	Weekly # of Apps in Master Schedule	Weekly Apps Lost to Employee Vacation	Weekly Apps Lost to Holidays	Weekly Apps lost due to Employees Away from Work	Expected # of Weekly Bookable Apps (Rounded Down)
Mon	RPT	New	11	0.6	0.5	0.6	9
		Return	97	5.6	4.5	4.9	82
	VMPT	New	6	0.3	0.3	0.3	5
		Return	89	5.1	4.1	4.5	75
	CPT	New	3	0.2	0.1	0.2	3
		Return	46	2.7	2.1	2.3	39
	DPT	New	4	0.2	0.2	0.2	3
		Return	51	2.9	2.4	2.6	43
Tue	RPT	New	10	0.6	0.5	0.5	8
		Return	112	6.5	5.2	5.6	95
	VMPT	New	5	0.3	0.2	0.3	4
		Return	102	5.9	4.7	5.1	86
	CPT	New	2	0.1	0.1	0.1	2
		Return	30	1.7	1.4	1.5	25
	DPT	New	4	0.2	0.2	0.2	3
		Return	53	3.1	2.4	2.7	45
Wed	RPT	New	12	0.7	0.6	0.6	10
		Return	94	5.4	4.3	4.7	80
	VMPT	New	3	0.2	0.1	0.2	3
		Return	74	4.3	3.4	3.7	63
	CPT	New	3	0.2	0.1	0.2	3
		Return	46	2.7	2.1	2.3	39
	DPT	New	3	0.2	0.1	0.2	3
		Return	48	2.8	2.2	2.4	41
Thu	RPT	New	9	0.5	0.4	0.5	8
		Return	93	5.4	4.3	4.7	79
	VMPT	New	8	0.5	0.4	0.4	7
		Return	88	5.1	4.1	4.4	74
	CPT	New	2	0.1	0.1	0.1	2
		Return	30	1.7	1.4	1.5	25
	DPT	New	5	0.3	0.2	0.3	4
		Return	53	3.1	2.4	2.7	45
Fri	RPT	New	10	0.6	0.5	0.5	8
		Return	104	6.0	4.8	5.2	88
	VMPT	New	4	0.2	0.2	0.2	3
		Return	85	4.9	3.9	4.3	72
	CPT	New	3	0.2	0.1	0.2	3
		Return	46	2.7	2.1	2.3	39
	DPT	New	3	0.2	0.1	0.2	3
		Return	52	3.0	2.4	2.6	44
			1503				**1272**

Capacity

An high-level capacity calculation was completed to provide contest for the ability of the network to handle its demand. The analysis is show in Table 4. The results suggest that CPT and DPT have more demand than supply, VMPT has more supply than demand, and that RPT may be operating with a stable capacity. In aggregate, the network supply of appointments approximately equals capacity.

Table 4: Calculation of supply and demand

	Number of referrals from Jan 1st 2017 - Sept 28th 2018	Approximate Weekly Number of Referrals	Approximate Weekly Number of New Appointments
RPT	4532	50	52
VMPT	898	10	26
CPT	1862	21	13
DPT	2989	33	19
		113	**110**

Appointment Attendance

There are several factors influencing the throughput of patients actually attending appointments. As is common in healthcare and especially outpatient clinics, no show and cancellation rates are high. Figure 8 shows the no-show and cancellation rates for the four clinics.

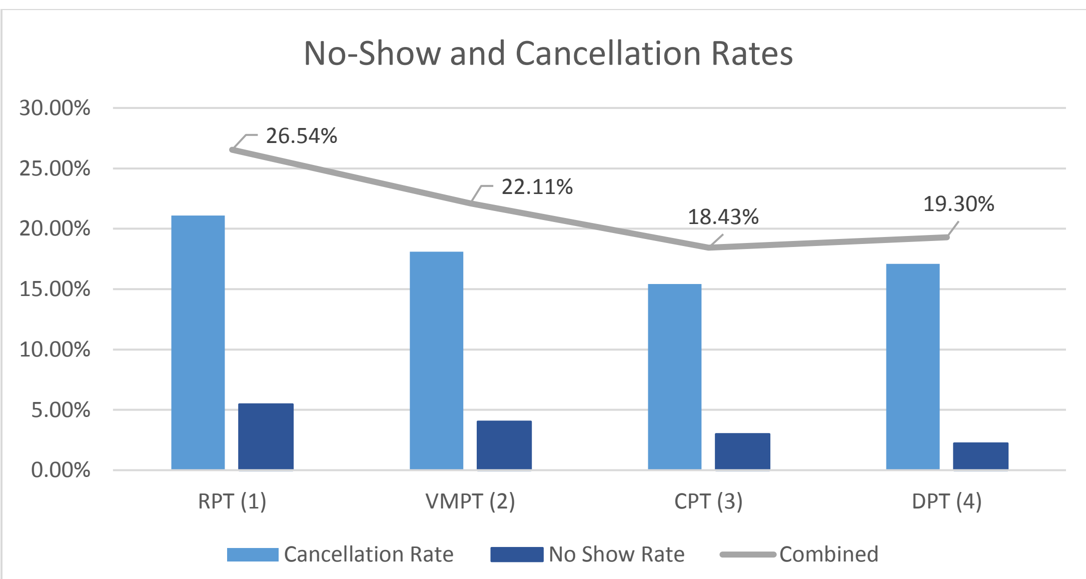

Figure 8: Analysis of no-show and cancellation rates

As was discussed in the literature review section, high no-show and cancellation rates have adverse impacts on the flow of a clinic, throughput, and also the patient's recovery. In the model described in Chapter 5, we assume that patients who do not attend their appointments will have to make up for that missed appointment at some point, and do not simply skip an appointment in their follow-up treatment.

Chapter 4: Model Parameters

This chapter provides information about the variables and attributes for each Macro. It should help the reader to understand the Macro explanations in Chapter 5. Most attributes are user-inputted, meaning the user can change them in a data table. The variables and attribute explanations are grouped by Macro. The same attribute, e.g. a patient's priority, could have different names in different Macros. Tables 5 through 10 specifies the parameters and input data used in the Generate Patients Macro, the Generate Schedule Macro, Schedule Patients Macros, and the Wait Time Dashboard Macro.

Table 5: Generate Patients Macro parameters

PatientListLength	Specifies the number of patients the user wishes to simulate.
j	Keeps track of time throughout the model. It is initialized as today's date.

Table 6: Input data for Generate Patient Macro

Mean Number of Return Appointments (user-inputted)	Specifies the mean number of return appointments for each type (priority and location) of patient.
Mean Number of Days in between Return Appointments (user-inputted)	Specifies the mean number of days in between return appointments for each type (priority and location) of patient.
Location Distribution (user-inputted)	Specifies the portion of patients that originate from each location.
Priority Distribution by Location (user-inputted)	Specifies the priority mix of patients for each location.
Arrival Distributions by Location	Empirical distributions for inter-arrival times for new referrals for each location.

Table 7: Generate Schedule Macro parameters

NumWeeks	The number of weeks' worth of appointments the Macro will prepare
Weekday	The day of week. Exists to allow the Macro the skip through weekends.
Loc	Appointment location
NorR	Appointment type, New or Return
NumSlots	The number of each type of appointment

Table 8: Input data for Generate Schedule Macro

Number of appointments for each type and location (user-inputted)	Represents the daily number of each type of appointment for each location.
Filled Appointment Rate (user-inputted)	Determines the number of appointments that will actually go filled and used. The utilization accounts for the number of appointments that are actually available to be booked and the number of appointments that go unused due to patients failing to attend appointments, or due to scheduling inefficiencies.

Table 9: Schedule Patients Macro parameters

AppointmentListLength	Keeps track of the size of the list of bookable appointments.
StarPntID	Star Patient's, meaning the patient subject to being scheduled throughout the model, unique identifier. It is a six digit number generated randomly.
StarPntNR	Star Patient's appointment type status. The patient is either a new or returning patient.
StarPntLoc	Star Patient's location. It ranges from 1-4.
StarPntPri	Star Patient's priority. It ranges from 1-4, representing Urgent, Priority 1, Priority 2 and General patients, respectively.
StarPntAD	Star Patient's arrival date. For new patients, this is the date they originally joined the waiting list. For return patients, is it the date of their most recent appointment, i.e. the date they joined the queue again to wait for an appointment.
StarPntFU	Star Patient's required number of follow-ups, which was given according to a historical distribution.

Table 10: Wait time dashboard Macro

Pri	The patient's priority.
Locat	The patient's location.
Wait time to first appointment	The number of days between the first date that the patient required the appointment (referral date for new patients, date of last appointment for return patients), and the date that the patient attended the appointment. This measure is calculated for each type of patient for each location.

Chapter 5: Model Development

Discrete event simulation was chosen as the most appropriate tool to model the network. Simulation was preferable because it meant that the scheduling policy could easily be changed throughout the analysis. Further, it would allow the user to change variables in the future such as number of appointments, mix of new and return appointments, number of clinics, etc. Finally, as described in Chapter 2, simulation was known to be an effective tool for studying outpatient scheduling because it allows the user to compare different scenarios against the current state. Further, simulation is an effective tool when there is stochastic uncertainty in a system, such as the volume of patient arrivals.

Overview and Assumptions

The premise of the simulation model is to generate a demand for appointments, generate a schedule of appointments, book patients in to the appointments, and measure the wait times. Patients are generated using the Generate Patients Macro. The schedule is generated using the Generate Schedule Macro. Patients are scheduled in to appointments using the Schedule Patients Macros. The wait times are measured using the Wait Time Dashboard Macro. Figure 9 shows the logic of the model. A feature of the simulation is that it allows the user to change the scheduling policy and measure how this change would impact wait times.

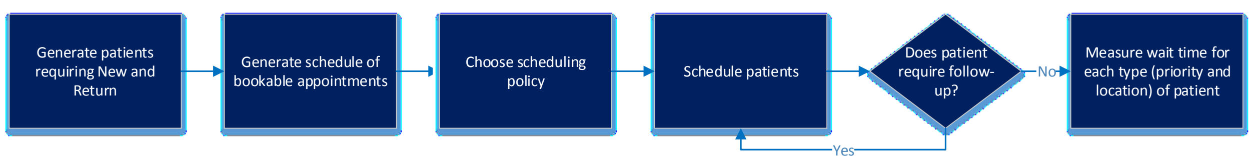

Figure 9: Model flow diagram

Scheduling decisions are made by clerical staff at each location. Generally, the current state scheduling policy is that high priority patients are seen first and that lower priority patients are only scheduled if no patients of higher priority require an appointment. During consultation with clerical staff, it was acknowledged that this policy might be informally broken, based on the judgement of clerical staff, from time to time.

Generate Patients Macro Overview

The Generate Patients Macro (Figure 10) allows the user to generate a user-specified number of patients requiring service. The purpose of this macro is to generate demand for appointments. The patients originate from one of the four hospitals, carrying this attribute with them throughout the model. The patients have a priority, target window to be seen within, and a required number of follow-ups. These attributes are based on data from the patient's origin hospital and priority. In this application this means there are 16 (four locations and four priorities) patient types.

Generate Patients Macro Code Explained

```
'generate as many patients as specified
Do While i <= PatientListLength

'Use a Random Number to give each patient a unique ID
wsA.Cells(i + 1, 1) = Rnd()
wsA.Cells(i + 1, 2) = Int((199999 - 100000 + 1) * Rnd + 100000)
'Initially, each patient arrives to the wait list as a new patient
wsA.Cells(i + 1, 3) = 1

'use random number to generate location according to distribution
If wsA.Cells(i + 1, 1) > wsC.Cells(4, 11) Then
    wsA.Cells(i + 1, 4) = 4
ElseIf wsA.Cells(i + 1, 1) > wsC.Cells(3, 11) Then
    wsA.Cells(i + 1, 4) = 3
ElseIf wsA.Cells(i + 1, 1) > wsC.Cells(2, 11) Then
    wsA.Cells(i + 1, 4) = 2
Else
wsA.Cells(i + 1, 4) = 1
End If
```

Figure 10: Generate Patient Macro Excerpt 1

The macro generates as many patients as are specified by the user, each with a unique identifier. Patients arrive at the wait list as new patients, meaning that their *NewOrReturn* attribute is "1". This becomes important later in the code, where New and Return Patients experience different operations. A New Patient is given a location, according to an empirical distribution generated from historical data.

```
'Use random number to assign priority based on location,
'then # of followups and time in between based on priority and location
wsA.Cells(i + 1, 5) = Rnd

If wsA.Cells(i + 1, 4) = 4 Then
    If wsA.Cells(i + 1, 5) > wsC.Cells(16, 3) Then
    wsA.Cells(i + 1, 6) = 4
    wsA.Cells(i + 1, 12) = wsC.Cells(17, 4)
    wsA.Cells(i + 1, 13) = wsC.Cells(17, 5)
    ElseIf wsA.Cells(i + 1, 5) > wsC.Cells(15, 3) Then
    wsA.Cells(i + 1, 6) = 3
    wsA.Cells(i + 1, 12) = wsC.Cells(16, 4)
    wsA.Cells(i + 1, 13) = wsC.Cells(16, 5)
    ElseIf wsA.Cells(i + 1, 5) > wsC.Cells(14, 3) Then
    wsA.Cells(i + 1, 6) = 2
    wsA.Cells(i + 1, 12) = wsC.Cells(15, 4)
    wsA.Cells(i + 1, 13) = wsC.Cells(15, 5)
    Else
    wsA.Cells(i + 1, 6) = 1
    wsA.Cells(i + 1, 12) = wsC.Cells(14, 4)
    wsA.Cells(i + 1, 13) = wsC.Cells(14, 5)
    End If
End If
```

Figure 11: Generate Patient Macro Excerpt 2

Patients are given a location-dependent priority according to an empirical distribution based on historical priority volumes for each location (Figure 5). Using the patient's location and priority, a required number of follow-ups and time between follow-ups is given. Again, these attributes are generated according to an empirical distribution of historical data.

```
'use random number to determine interarrival time, based on location
wsA.Cells(i + 1, 7) = Rnd()

If wsA.Cells(i + 1, 4) = 1 Then
    wsA.Cells(i + 1, 8) = WorksheetFunction.VLookup(wsA.Cells(i + 1, 7), wsB.Range("G3:H18"), 2, True)
ElseIf wsA.Cells(i + 1, 4) = 2 Then
    wsA.Cells(i + 1, 8) = WorksheetFunction.VLookup(wsA.Cells(i + 1, 7), wsB.Range("I3:J18"), 2, True)
ElseIf wsA.Cells(i + 1, 4) = 3 Then
    wsA.Cells(i + 1, 8) = WorksheetFunction.VLookup(wsA.Cells(i + 1, 7), wsB.Range("K3:L18"), 2, True)
Else
wsA.Cells(i + 1, 8) = WorksheetFunction.VLookup(wsA.Cells(i + 1, 7), wsB.Range("M3:N18"), 2, True)
End If
```

Figure 12: Generate Patient Macro Excerpt 3

The inter-arrival time between patients is determined according to an empirical arrival pattern which was generating according to historical data. A patient's location determines which distribution to use, as each location has a separate arrival pattern.

```
'the first patient in the list will arrive at j,
'subsequent patients will arrive at j + interarrival time
If i > 1 Then
    wsA.Cells(i + 1, 9) = wsA.Cells(i, 9) + wsA.Cells(i + 1, 8)
Else
wsA.Cells(2, 9) = j
End If
```

Figure 13: Generate Patient Macro Excerpt 4

The macro begins by creating the first patient on today's date. Following patients arrive according to the inter-arrival times which were generated in the previous step.

Generate Schedule Macro Overview

The Generate Schedule Macro allows the user to generate the master schedule of bookable appointments at all four hospitals for a time horizon of their choosing. Originally, the actual weekly master schedule (approximately 1500 appointments) was manually generated in Excel. While using the actual schedule was beneficial because it allowed the client to see their actual schedule in the model, thus gaining confidence in it, it became very difficult to maintain the master schedule throughout the project. Slight schedule changes occurred throughout the project, each requiring manual effort to modify and reorganize the schedule. Finally, it became too difficult to maintain the master schedule and a different approach was taken. The Generate Schedule Macro was created to generate a master schedule that is representative, meaning having the same volume and type of appointments, as the true master schedule. The schedule can be easily modified. The user can increase or decrease the amount of New and Return appointments at all four locations and test the resulting impact on wait times.

Generate Schedule Macro Explained

```
For i = 1 To NumWeeks

    For Weekday = 1 To 5

        If Weekday = 1 Then
        k = k + 3
        Else
        k = k + 1
        End If
```

Figure 14: Generate Schedule Macro Excerpt 1

The user initially specifies how many weeks' worth of a master schedule they would like to generate. The first portion of the code keeps track of today's date (*k*), skipping through Saturday and Sunday on the weekends.

```
For Loc = 1 To 4

    For NorR = 0 To 1

        For Roww = 2 To lRow

            If Cells(Roww, 1) = Weekday And Cells(Roww, 2) = Loc And Cells(Roww, 3) = NorR Then
                NumSlots = Cells(Roww, 4)
                Exit For
            End If

        Next Roww
```

Figure 15: Generate Schedule Macro Excerpt 2

The Macro must search for the number of each type of appointment (New and Return) for each location. For locations 1 through 4, the code reads through the Location, Weekday, and Appointment type, searches the master table for the right number of appointments, and stores this number as *NumSlots*.

```
                    For j = 1 To NumSlots

                    CurrentRow = CurrentRow + 1

                    wsA.Cells(CurrentRow, 1) = Loc
                    wsA.Cells(CurrentRow, 2) = NorR
                    wsA.Cells(CurrentRow, 3) = k

                    Next j

                Next NorR

            Next Loc

        Next Weekday

    Next i
```

Figure 16: Generate Schedule Macro Excerpt 3

For as many appointments of each type, the Macro generates the actual schedule, printing out the Location, Appointment Type, and Date. This loop populates the master schedule for as many weeks as was specified. The appointment time is not important because wait times are measured in terms of full days. It is only important to generate the correct daily number of appointments of each type and for each location. It is not important to arrange these appointments throughout the day.

Schedule Patients Macros and Varying Policies Overview

The most interesting components of the model are the various scheduling policies, based on various queuing disciplines, which can be used to schedule patients into appointments. The user can select which scheduling policy they want to use to schedule patients and predict the outcome of their decision before they make it.

Policy 1: Patient priority is ignored. Patients are scheduled according to the earliest arrival date, to their home location.

Policy 2: Patient priority is ignored. Patients are scheduled according to the earliest arrival date, to any location.

Policies 1 and 2 are were modeled to help validate the model and create bounds for results. They represent classical FCFS queueing policies. The third policy is a classical priority queuing discipline and represents the current state of the scheduling process, where patients of highest priority are scheduled first, in order of earliest arrival date.

Policy 3 (Current State): Patients are first sorted by priority, then by earliest arrival date. Patients are scheduled to their home location.

Policies 4 and 5 are the practical policies that management is actually considering implementing. These policies take in to account that high priority patients have likely just undergone surgery and should be seen at their origin hospital as soon as possible. Low priority patients may have to travel to a clinic with a shorter wait time.

Policy 4: Patients are first sorted by priority, then by earliest arrival date. Patients can be scheduled to any location.

Policy 5: Patients are sorted by priority, then by earlier arrival date. Urgent and Priority 1 patients must be scheduled to their home location. Priority 2 and General patients can be scheduled to any location.

Schedule Macro Explained – Policy 1

```
'while there is at least one patient requiring followup
Do While wsP.Cells(18, 14) > 0

    'sort patient list by arrival date
    Range("A2:M1000").Select
    ActiveWorkbook.Worksheets("Patients").Sort.SortFields.Clear
    ActiveWorkbook.Worksheets("Patients").Sort.SortFields.Add Key:=Range("I2:I1000" _
        ), SortOn:=xlSortOnValues, Order:=xlAscending, DataOption:=xlSortNormal
    With ActiveWorkbook.Worksheets("Patients").Sort
        .SetRange Range("A1:M1000")
        .Header = xlYes
        .MatchCase = False
        .Orientation = xlTopToBottom
        .SortMethod = xlPinYin
        .Apply
    End With
```

Figure 17: Scheduling Macro Excerpt 1

The condition that must be satisfied to begin executing the code is for at least one patient to require an appointment. Once all patients have scheduled all appointments, the end condition is met and the code terminates. For Policy 1, the patient list is sorted according to arrival date. Arrival date means the time that the patient arrives at the wait list. For new patients, it is their referral date and for returning patients, it is the date of their last appointment, when they first required their next appointment. Each time a patient is scheduled, the list is re-sorted by arrival date.

```
    k = 1

    'if first patient in list requires followup
FIND_STARPATIENT:
    If wsP.Cells(k + 1, 12) > 0 Then

        'set first patient in list to be star patient
        StarPntID = wsP.Cells(k + 1, 2)
        StarPntNR = wsP.Cells(k + 1, 3)
        StarPntLoc = wsP.Cells(k + 1, 4)
        StarPntPri = wsP.Cells(k + 1, 6)
        StarPntAD = wsP.Cells(k + 1, 9)
        StarPntFU = wsP.Cells(k + 1, 12)

    'otherwise set next patient to be star patient
    Else
        k = k + 1
    If wsP.Cells(18, 14) > 0 Then GoTo FIND_STARPATIENT

    End If
```

Figure 18: Scheduling Macro Excerpt 2

The algorithm keeps track of the earliest-arriving patient that requires a follow-up appointment and calls this patient the Star Patient. If every patient on the list requires follow-up, the Star Patient is in the first row because the patients have already been sorted by arrival date. As patients receive follow-up appointments and eventually finish their treatment, the Star Patient moves down row by row, until no patients require follow-up and the algorithm is complete.

```
j = 1

'while j is less than the number of appointments
Do While j <= AppointmentListLength

    'If appointment slot is empty, appointment date is after patient's arrival date and patient is a match
    If wsA.Cells(2 + j, 4) = "" And wsA.Cells(2 + j, 1) = StarPntLoc And wsA.Cells(2 + j, 2) = StarPntNR And wsA.Cells(2 + j, 3) > StarPntAD Then

        'Schedule patient
        wsA.Cells(2 + j, 4) = StarPntID
```

Figure 19: Scheduling Macro Excerpt 3

Once the algorithm has identified the Star Patient, it must find a suitable appointment. It searches through the appointment book to find a match. Once it finds the first empty slot that is both the correct type and is later than the patient's arrival date, the algorithm chooses this appointment and schedules the patient.

```
'Record patient's arrival date
wsA.Cells(2 + j, 5) = StarPntAD

'Record patient's priority
wsA.Cells(2 + j, 6) = StarPntPri

'Record wait time
If StarPntNR > 0 Then
    wsA.Cells(2 + j, 7) = wsA.Cells(2 + j, 3) - wsA.Cells(2 + j, 5)
End If
```

Figure 20: Scheduling Macro Excerpt 4

The code records the patient's priority and arrival date. These attributes will be helpful later when calculating wait times according to each type of patient.

```
    'Update patient in patient queue
    If wsP.Cells(k + 1, 3) = 1 Then 'If patient is new
        wsP.Cells(k + 1, 11) = wsP.Cells(k + 1, 13) 'After their first appointment,
        wsP.Cells(k + 1, 3) = 0 'Update NR be a return patient
    End If

    'Update date to be appointment date plus target window
    wsP.Cells(k + 1, 9) = wsA.Cells(2 + j, 3) + wsP.Cells(k + 1, 11)

    'Reduce # of followups by 1
    wsP.Cells(k + 1, 12) = wsP.Cells(k + 1, 12) - 1 'Reduce # of followups by 1

    j = AppointmentListLength + 1 'Exit Do

Else
    j = j + 1

End If
```

Figure 21: Scheduling Macro Excerpt 5

After their first appointment, patients complete the follow-up appointments. The inter-arrival time for follow-up appointments is generated according to historical data from each location. A patient's required number of follow-up appointments is reduced by one each time they are seen until they have completed all their appointments and no longer require follow-up.

Schedule Macro Explained – Policy 2

```
'If appointment slot is empty, appointment date is after patient's arrival date and patient is a match
If wsA.Cells(2 + j, 8) = "" And wsA.Cells(2 + j, 2) = StarPntNR And wsA.Cells(2 + j, 3) > StarPntAD Then
```

Figure 22: Schedule Macro Policy 2 Excerpt 1

The only difference in the code for Policy 2 is that the location requirement is excluded. Patients are only matched to the correct type of appointment. It is not required that a patient visits their home location.

Schedule Macro Explained – Policy 3

```
'sort patient list by priority
Range("A2:M1000").Select
ActiveWorkbook.Worksheets("Patients").Sort.SortFields.Clear
ActiveWorkbook.Worksheets("Patients").Sort.SortFields.Add Key:=Range("F2:F1000" _
    ), SortOn:=xlSortOnValues, Order:=xlAscending, DataOption:=xlSortNormal
With ActiveWorkbook.Worksheets("Patients").Sort
    .SetRange Range("A1:M1000")
    .Header = xlYes
    .MatchCase = False
    .Orientation = xlTopToBottom
    .SortMethod = xlPinYin
    .Apply
End With
```

Figure 23: Schedule Macro Policy 3 Excerpt 1

The difference in the code for Policy 3 is that the list of patients is re-sorted every time according to Priority instead of Arrival Date. Patients are sequenced for scheduling first according to their priority, and secondly by their order of arrival.

Schedule Macro Explained – Policy 4

```
'sort patient list by priority
Range("A2:M1000").Select
ActiveWorkbook.Worksheets("Patients").Sort.SortFields.Clear
ActiveWorkbook.Worksheets("Patients").Sort.SortFields.Add Key:=Range("F2:F1000" _
    ), SortOn:=xlSortOnValues, Order:=xlAscending, DataOption:=xlSortNormal
With ActiveWorkbook.Worksheets("Patients").Sort
    .SetRange Range("A1:M1000")
    .Header = xlYes
    .MatchCase = False
    .Orientation = xlTopToBottom
    .SortMethod = xlPinYin
    .Apply
End With
```

Figure 24: Schedule Macro Policy 4 Excerpt 1

Patients are sequenced the same way in Policy 4 as in Policy 3: first by priority, and second by arrival date.

```
'If appointment slot is empty, appointment date is after patient's arrival date and patient is a match
If wsA.Cells(2 + j, 16) = "" And wsA.Cells(2 + j, 2) = StarPntNR And wsA.Cells(2 + j, 3) > StarPntAD Then
```

Figure 25: Schedule Macro Policy 4 Excerpt 2

Patients are scheduled the same way in Policy 4 as in Policy 2: patients need not attend their origin hospital for their appointment.

Schedule Macro Explained – Policy 5

```
'If patient's priority is 1 or 2, include location
If StarPntPri < 3 Then
```

Figure 26: Schedule Macro Policy 5 Excerpt 1

Policy 5 requires that a patient's location be a match only for Urgent and Priority 1 patients. Priority 2 and General patients can travel to any location for their appointment.

Wait Time Dashboard

The wait time dashboard displays the wait time for new patients for all priorities and locations.

```
For i = 4 To 7
    For j = 2 To 11 Step 3
        Pri = (j + 1) / 3
        Locat = i - 3
        wsA.Cells(i, j) = WorksheetFunction.CountIfs(wsB.Range("A3", "A10000"), "=" & Locat, wsB.Range("F3", "F10000"), "=" & Pri)
    Next j
Next i
```

Figure 27: Wait Time Dashboard Excerpt 1

The algorithm uses the relationship between the counting variables, *i* and *j*, and the attributes, *Pri* and *Locat*, to keep track of its location in the dashboard as it counts the number of appointments of each type.

```
For i = 4 To 7
    For j = 3 To 12 Step 3
        Pri = j / 3
        Locat = i - 3
        wsA.Cells(i, j) = WorksheetFunction.SumIfs(wsB.Range("G3", "G10000"), wsB.Range("A3", "A10000"), "=" & Locat, wsB.Range("F3", "F10000"), "=" & Pri)
    Next j
Next i
```

Figure 28: Wait Time Dashboard Excerpt 2

The algorithm records the sum of the wait times for the appointment type (priority and location) of interest.

```
For i = 4 To 7
    For j = 4 To 13 Step 3
            If wsA.Cells(i, (j - 2)) = 0 Then
                wsA.Cells(i, j) = "N/A"
            Else
                wsA.Cells(i, j) = wsA.Cells(i, (j - 1)) / wsA.Cells(i, (j - 2))
            End If
    Next j
Next i
```

Figure 29: Wait Time Dashboard Excerpt 3

The algorithm uses the count and sum of appointment types to calculate the mean waiting time for each appointment type.

Chapter 6: Model Validation, Calibration, and Warm-up Period

The model was tested and validated continuously throughout the lifecycle of the project. New additions in code required both functional and regression testing to ensure changes did not affect other working parts of the model. The goals of the validation tests were to verify that the model is performing as expected for various logical tests, e.g. a reduction in resources results in longer wait times. The goal of the calibration phase is to calibrate the model to reflect and generate the same waiting times as those generated in the current state scheduling process. All experiments detailed in this section reflect the current scheduling policy, Policy 3. Calibrating the model to reflect the current state allowed for a strong base case for analysis. Several experiments were conducted to determine the appropriate warm-up period and run length for this model. The run length is set by the user specifying the number of patients to generate.

Verification and Validation

The function of every algorithm was tested throughout the development of the model. It was important to test that the Generate Patients algorithm was correctly generating a list of patients with the same attributes as the actual historical patients. To test this, the descriptive statistics of the model-generated patients were compared against the descriptive statistics of the historical patients. The types of attributes that were tested were locations, priorities, number of return appointments, and time in between return appointments. Table 11 shows a comparison of model vs. actual priority mixes for each location. They are very close, as expected. The allocation of priorities is a stochastic process and so a small margin of error is expected.

Table 11: Comparison of Model vs Actual priority mixes by location

	Model					Actual			
	Urgent	Pri 1	Pri 2	General		Urgent	Pri 1	Pri 2	General
DPT	0.01	0.25	0.27	0.47	DPT	0.01	0.24	0.28	0.47
VMPT	0.45	0.39	0.07	0.09	VMPT	0.42	0.39	0.08	0.12
CPT	0.21	0.44	0.24	0.10	CPT	0.19	0.43	0.25	0.13
RPT	0.23	0.18	0.23	0.36	RPT	0.23	0.15	0.23	0.38

The Generate Schedule Macro must generate a schedule that is representative of the actual schedule. The exact times of appointments are not important, only that there are the correct number of New and Return appointments each day for each location. Table 12 shows a comparison of the desired schedule output and the model output. The generation of the schedule is a deterministic process so no margin of error is expected.

Table 12: Comparison of desired vs actual output of the number of New and Return appointments for each location

Desired Output

	RPT		VMPT		CPT		DPT	
Weekday	Return	New	Return	New	Return	New	Return	New
1	49	6	45	3	23	2	26	2
2	56	5	51	3	15	1	27	2
3	47	6	37	2	23	3	24	2
4	47	5	44	4	15	1	27	3
5	52	5	43	2	23	2	26	2

Actual Model Output

	RPT		VMPT		CPT		DPT	
Weekday	Return	New	Return	New	Return	New	Return	New
1	49	6	45	3	23	2	26	2
2	56	5	51	3	15	1	27	2
3	47	6	37	2	23	2	24	2
4	47	5	44	4	15	1	27	3
5	52	5	43	2	23	2	26	2

Experiments

Several experiments were conducted in an attempt to determine the filled appointment rate and warm-up period for the model. These experiments served as further validation tools for the model. The experiments were all conducted using Policy 3. The filled appointment rate and run length were varied.

Experiment 1: Filled Appointment Rate

The goal of this experiment was to determine the best filled appointment rate to use during the analysis portion of the project. As described in Chapter 5, the Generate Schedule Macro uses a user-specific filled appointment rate to determine how many of the total master appointments to allow to be booked in the schedule. The difference between the bookable appointment rate and filled appointment rate is that the filled appointment rate accounts for missed appointments. Filled appointment rates ranging from 20% to 100% were tested for each location. The goal is to calibrate the model as best as possible to the current state to generate a good base case for analysis. A 100% attended appointment rate is not actually possible in the real world. It would mean that employees went to work every single day, never took vacation, every appointment went filled, and every patient showed up for their appointment. Determining the filled appointment rate accomplishes three goals:

- It allows the model to account for factors leading to appointments going unfilled described in Chapter 3, e.g. employee vacation.
- It allows the model to account for patients not showing up for appointments. The filled appointment rate should be less than the capacities determined in Chapter 3, because those did not account for the fact that patients will not show up for appointments.
- It allows the model to account for inaccuracies in schedule data. As was already mentioned, we have only a moderate degree of confidence in the master schedules as they arrived in various formats with varying information.

The model output results of varying the attended appointment rate for each location are presented in Figures 30 through 33. Each of Figures 30 through 33 show the expected wait time to first appointment for the four priorities at each separate location. Care should be taken to take note of the different y-axis scales.

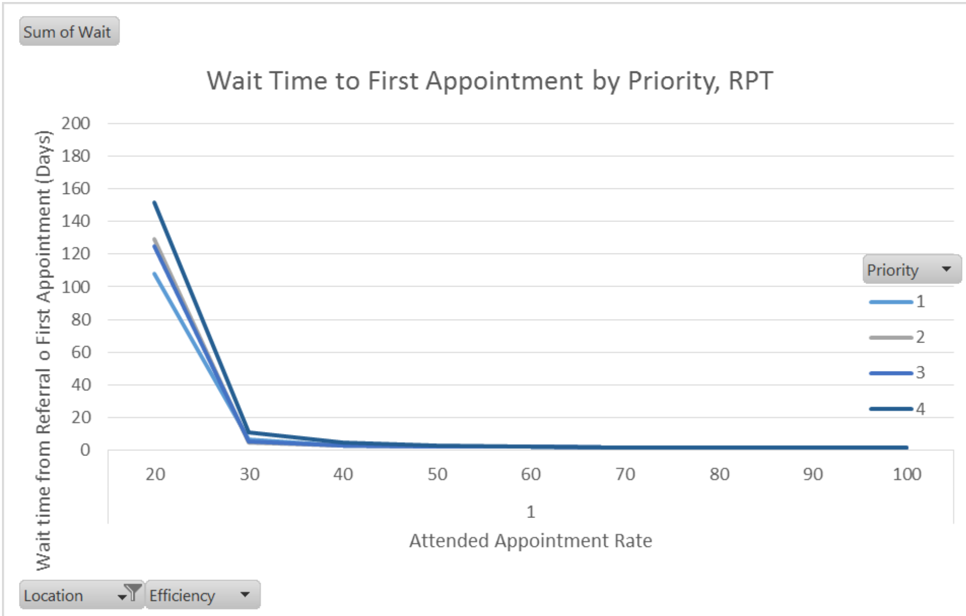

Figure 30: Wait time to first appointment for RPT. The four colours represent the four priorities. Attended appointment rate is varied from 20%-100%

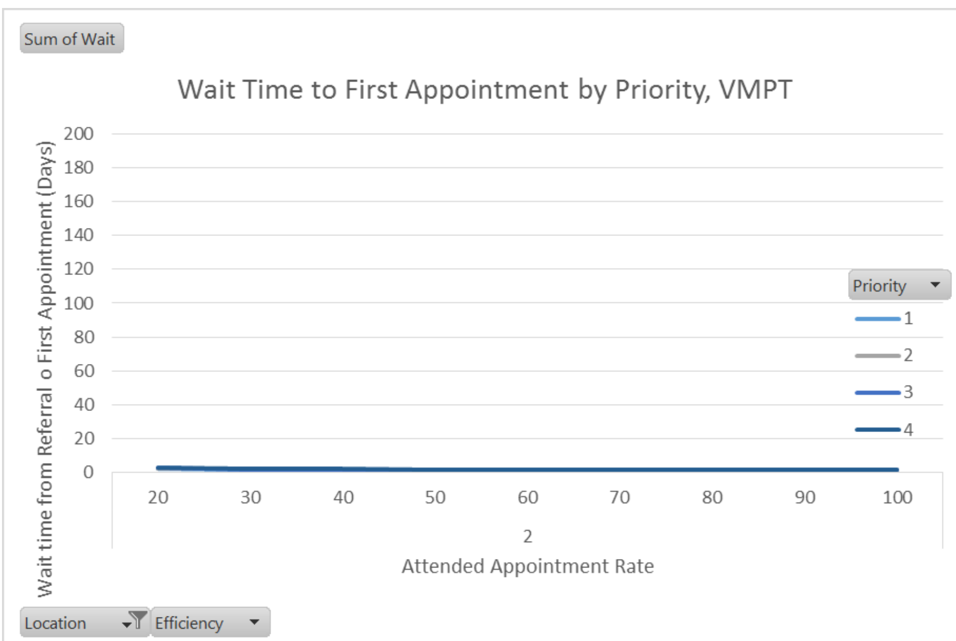

Figure 31: Wait time to first appointment for VMPT. The four colours represent the four priorities. Attended appointment rate is varied from 20%-100%

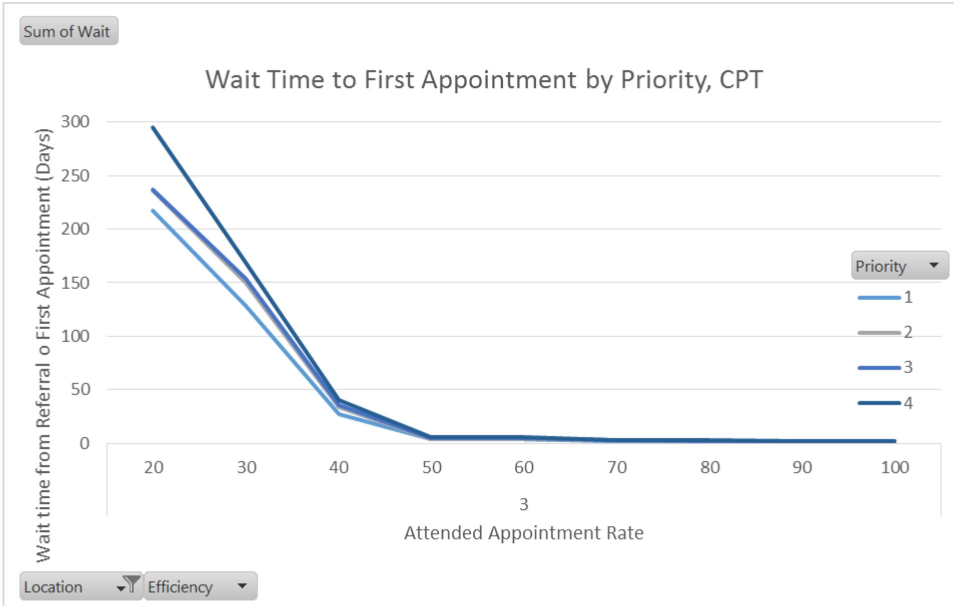

Figure 32: Wait time to first appointment for CPT. The four colours represent the four priorities. Attended appointment rate is varied from 20%-100%

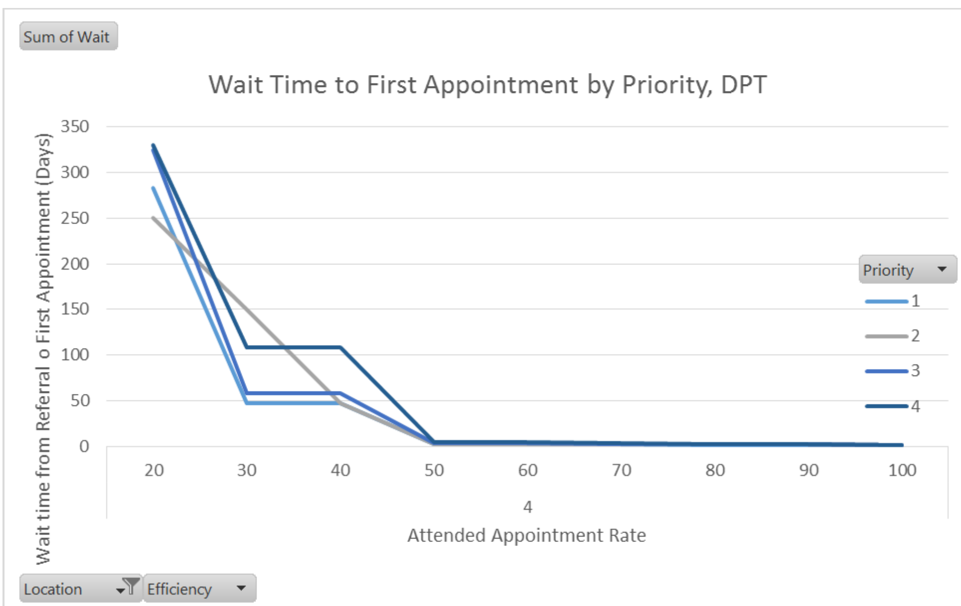

Figure 33: Wait time to first appointment for DPT. The four colours represent the four priorities. Attended appointment rate is varied from 20%-100%

The results show that VMPT effectively never experiences a wait time, suggesting that it has more capacity than demand. RPT only experiences a wait time when using a booked appointment rate of 30% or less. The results for CPT and DPT are more interesting. They begin to experience wait times similar to historical wait times at the 40% filled appointment rate. Historical wait times are shown again in Figure 34.

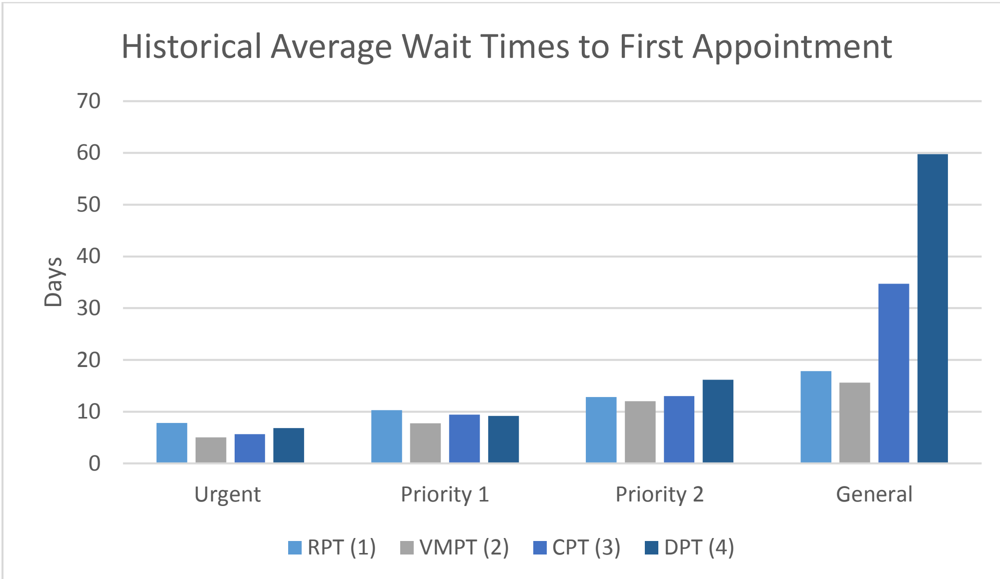

Figure 34: Historical wait times to first appointment

The results of this experiment serve two purposes. First, they help to validate the model. We would expect that the filled appointment rate should be even lower than the numbers described in Chapter 3 because patients do not show up for appointments. Table 13 uses the booked appointment rates calculated in Chapter 3 and the no-show rates for each location to determine a conservative estimate for what we would expect the filled appointment rate to be in the model.

Table 13: Expected attended appointment rates

Location	Total Wkly Appointments	Bookable App Rate (*Calculated in Chapter 3*)	Bookable App's (*Total Wkly App's Multiplied by Bookable Appointment Rate*)	Missed App Rate (*From Historical Data, Described in Chapter 3*)	Expected Filled Appointments (*Wkly Bookable App's Multiplied by (1-Missed App Rate*)	Expected Filled Appointment Rate (*Wkly Filled App's Divided by Total Weekly App's)*
RPT	552	85%	467	27%	343	62%
VMPT	464	85%	393	22%	306	66%
CPT	211	85%	179	18%	146	69%
DPT	276	85%	234	19%	188	68%

The expected filled appointment rate ranges from 62% to 69%. The results of this experiment showed that the actual filled appointment rate ranges from 40% to 50% because, as shown in Figures 30-33, this is when the wait times start to approach the historical wait times. There are several possible reasons for this variance, including inefficient scheduling methods, more employee absence than previously thought, or more employee time spent on other activities than patient care than previously thought, etc.

Second, the results provide further basis for exploration. The conclusion of this experiment is that further experiments should be conducted with a filled appointment rate of 40%. While RPT and VMPT do not experience wait times at this rate, using a lower rate may reduce their capacity to a point that the other locations would not be able to take advantage of it, which is important for some of the scheduling policies.

Experiment 2: 10 Repetitions of 3000 Patients

An initial patient number of 3000 was chosen as a starting point. 3000 patients was an approximate starting point because it represents approximately 20 months' worth of activity, which is the same length of time for which the historical data was analyzed. Ten repetitions of the simulation were completed and the results of this experiment are shown in Figure 35.

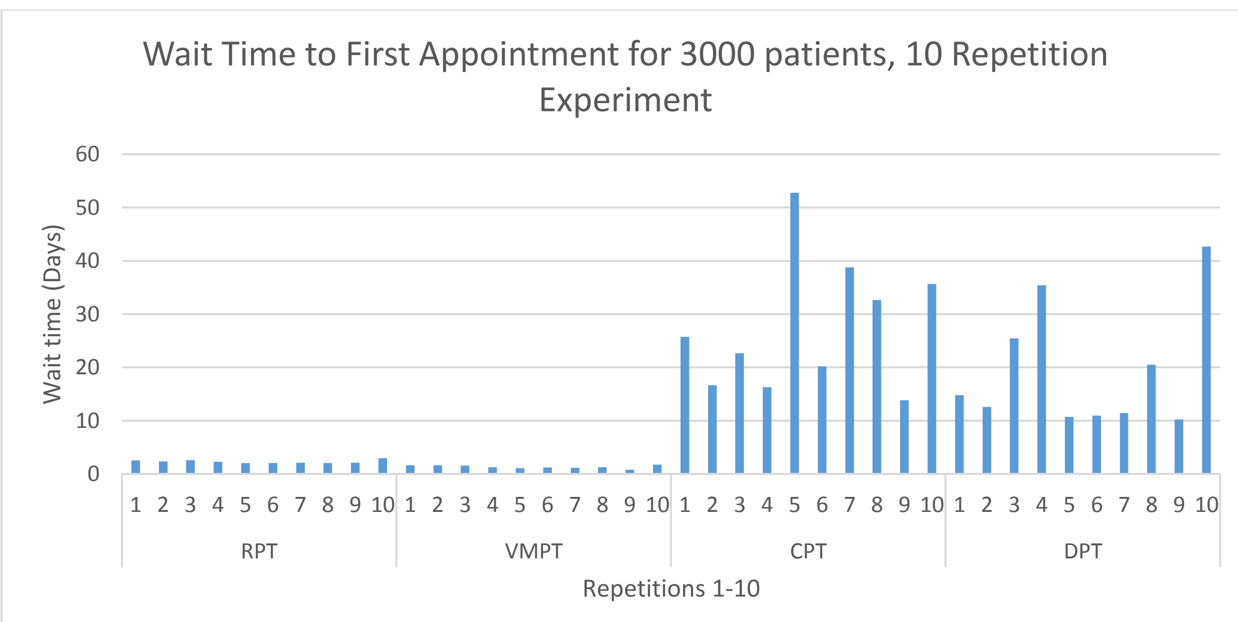

Figure 35: Wait time for first appointment for all priorities, for 3000 patients

It can be seen that two locations, RPT and VMPT, experience a short wait time with little variability in all 10 repetitions. This evidence suggests that RPT and VMPT have ample capacity to meet their demand because in every repetition their patients experienced very low waiting times. This result agrees with the historical wait times. CPT and DPT, the two locations with historically longer wait times, do not seem to reach a steady state within 20 months. Their wait times are comparable to historical wait times in some repetitions but are highly variable. It can be concluded that running the model for 20 months, simulating 3000 patients' worth of data, is not a sufficient run time for the CPT and DPT locations, but could be sufficient for RPT and VMPT.

Experiment 3: 1 Repetition of 9000 Patients

This experiment simulated 9000 patients, or approximately 6 years, worth of patients at 40% bookable appointment rate. Patients were only scheduled for their first appointment due to model run time constraints. Because the model involves a sorting algorithm, the run time can be extremely long and grow exponentially. For example, the run time for this experiment of scheduling 9000 patients for their first appointment was 4 hours. The focus of this experiment was low priority patients at DPT, which is the population experimenting the longest wait times and the original reason for undertaking this work. The results of the experiment are shown in Figure 36.

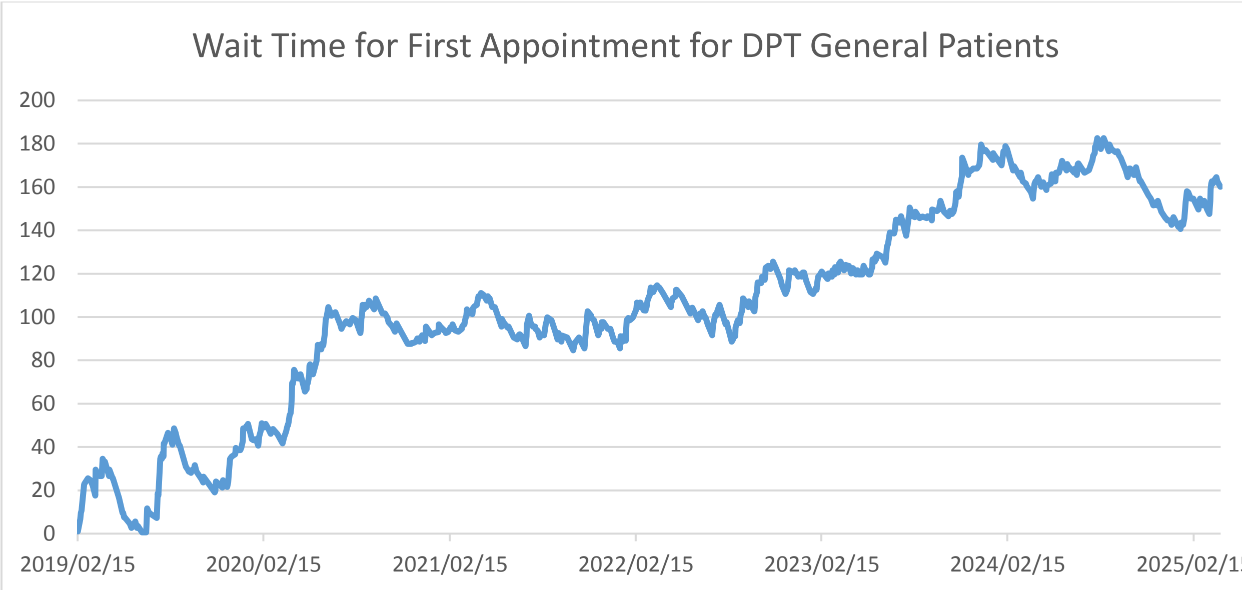

Figure 36: Wait time to first appointment for DPT General Patients, 6 year period

As is expected in a system with greater supply than demand, the wait times for this group of patients grew continuously and never reached a steady state. The volatility in wait time for this type of patient in the first 18 month period is agreeable with the conclusion reached in Experiment 2, that a run length of 18 months is not sufficient. Figure 37 compares the wait time to first appointment with the rate of change in wait times per day. While the wait time is increasing without bounds, the rate of change remains fairly constant after some initial volatility in the warm-up period.

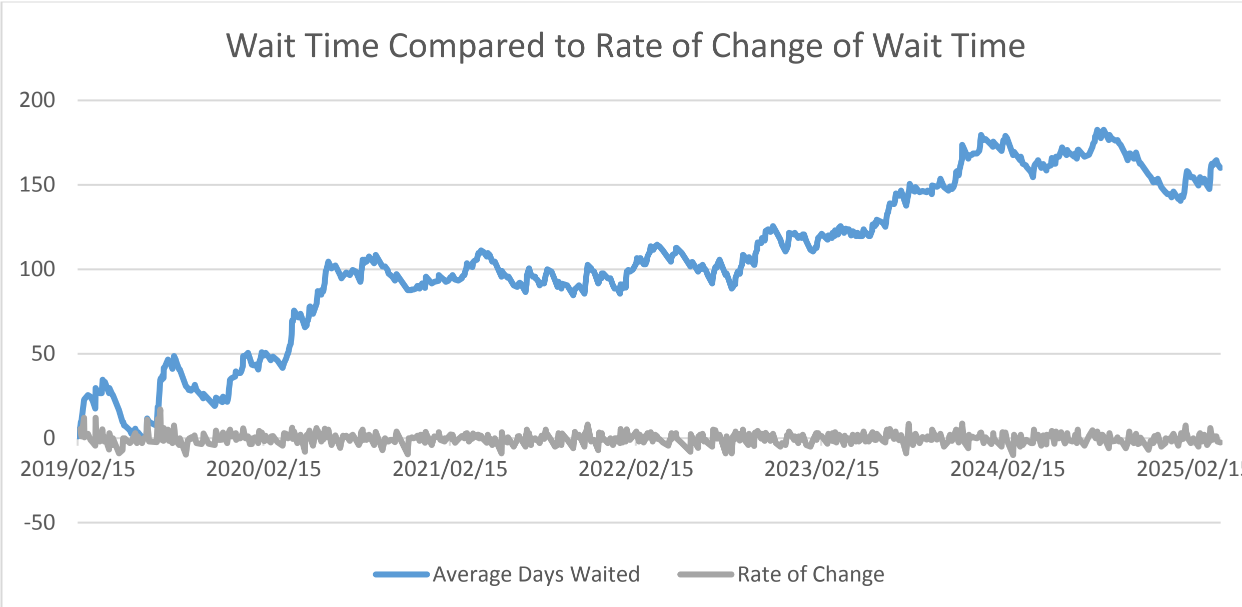

Figure 37: Wait time to first appointment compared to the rate of change in wait time

The conclusion of this experiment is that demand of appointments at DPT clearly exceeds supply and that the wait times will continue to grow until the problem is rectified. The model fails to reach a steady state for certain types of patients, even after a very long time period. This makes it very hard to determine an appropriate warm-up period and run length for the model.

Experiment 4: 8 Repetitions of 5000 Patients

For the fourth experiment, the model was run eight times for 5000 patients. The goal of the experiment was to explore the warm-up period. Figure 38 shows the average wait time to first appointment over eight repetitions for general patients at DPT. Each repetition experiences volatility in the first year, with wait times increasing and then decreasing. The wait times then grow without bound for subsequent years. The conclusion of this experiment is that the warm-up time for the model may be approximately one year but that future experimentation is required.

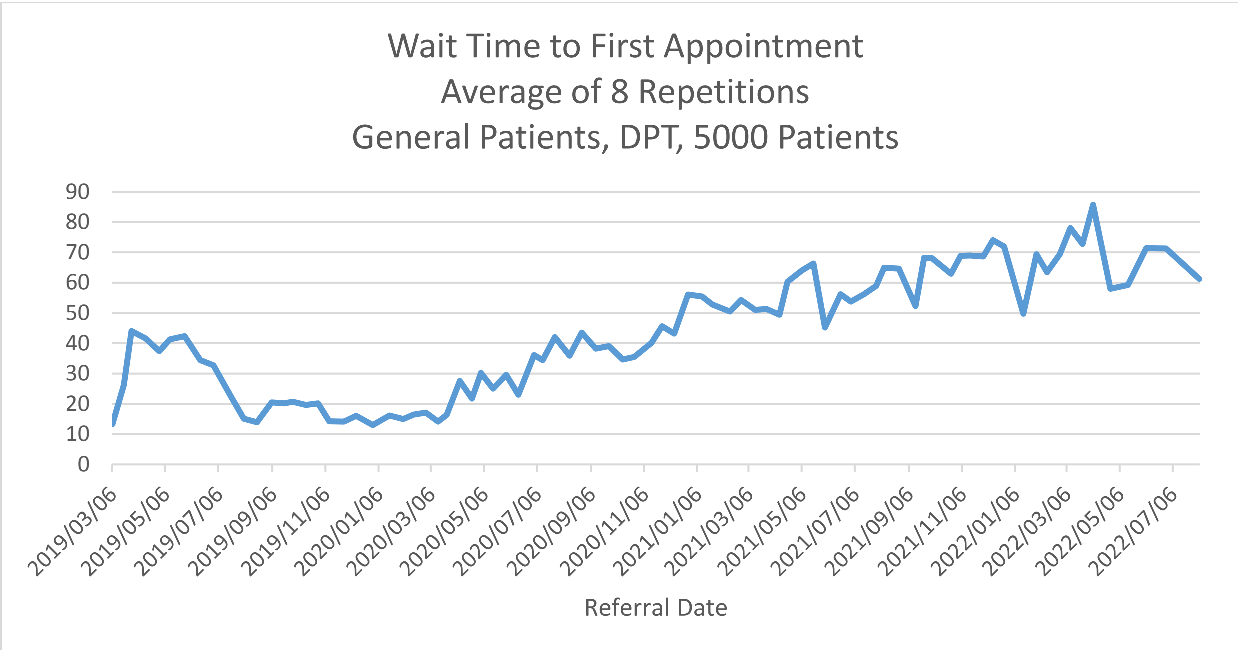

Figure 38: 8 repetitions of 5000 General DPT patients

Experiment 5: Comparing Wait Times for General Patients at All Locations

It was concluded in Experiment 4 that the wait times for some types of patients will never reach a steady state in the current state scheduling policy. Instead of trying to determine a warm-up period for the model using the wait times that never reach a steady state, it is possible to determine an appropriate warm-up period using wait times for patients that do reach steady state. Figure 39 shows the wait time to first appointment for General patients at each location for five repetitions of 5000 patients. The expected behavior of this model run is that patients at RPT and VMPT will experience very little wait time but that wait times for CPT and DPT will grow. The discontinuity in the trends represents the fact that General patients do not arrive every day at every location.

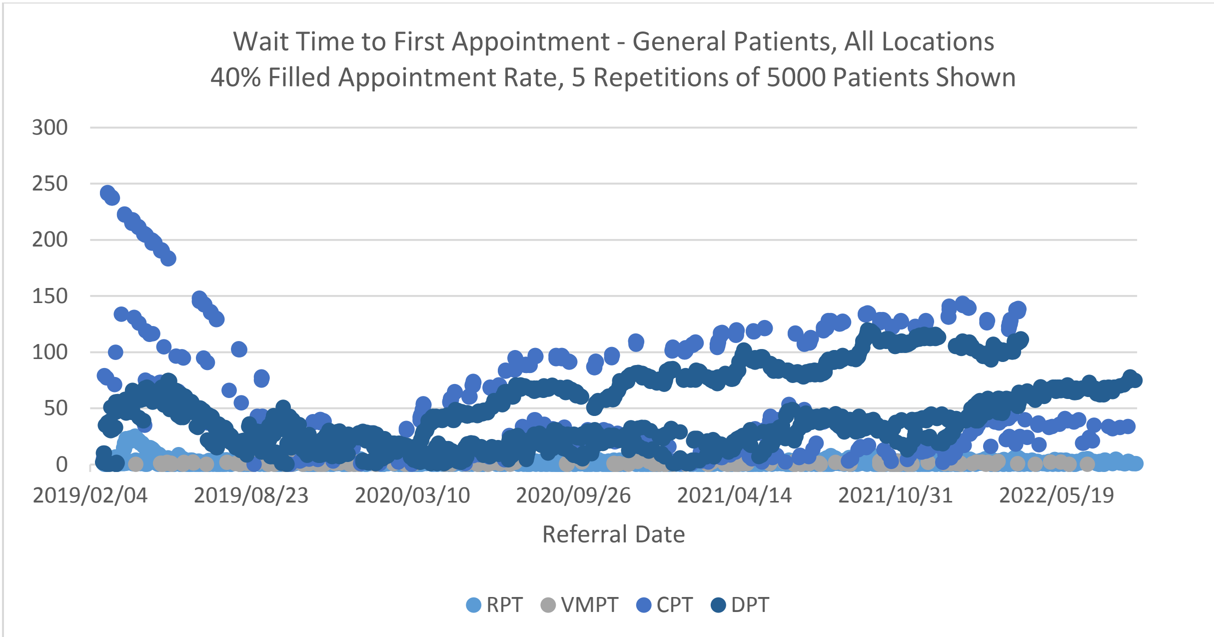

Figure 39: Comparison of wait time to first appointment for General patients at all locations

This figure is the first indication of a good warm-up period. RPT and CPT patients reach their steady state of almost no wait time very quickly. VMPT and DPT patients experience a warm-up period of about one year. The conclusion of this experiment is that the warm-up period shall be one year and that the results will be analyzed for the three subsequent years.

Chapter 7: Results

Scheduling Policies

Policy 1

Policy 1 represents the true First Come First Served queueing discipline, where a patient's priority is not considered. Patients can only attend appointments at their home location. As a result, patients from the same location should wait the same amount of time for their appointment. The results from the model are shown in Figure 40 and confirm the expectation: Wait times are the same for patients of different priority but coming from the same location. The conclusion that can be drawn here is that implementing a First Come First Served Policy, ignoring priority, could reduce wait time for low priority patients but to the detriment of high priority patients. This policy is not actually being considered by management. It was modeled to help validate the model and create bounds for results. The result can be interpreted such that RPT and VMPT have ample supply of appointments because there are no waiting times regardless of priority. CPT and DPT's wait times do not stabilize: their waiting times grow without bound. They do not have ample supply of appointments to accommodate their demand.

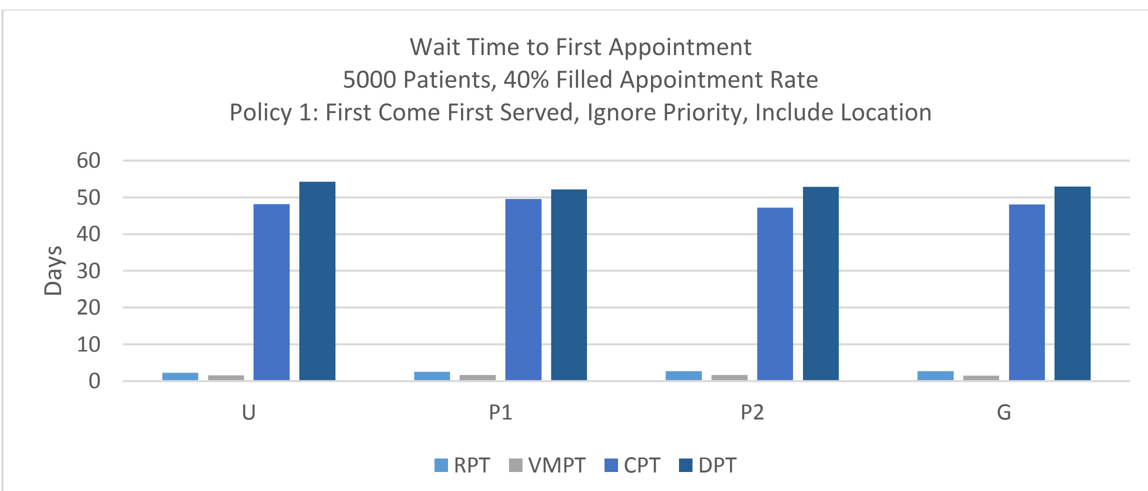

Figure 40: Average wait time to first appointment for all locations and all priorities, Policy 1

Policy 2

Policy 2 is the same as Policy 1, except that a patient's home location is not considered; they can be seen at any location. The queuing discipline is First Come First Served and location is ignored. The expected result for this Policy is that all patients should wait for the same amount of time, regardless of their location or priority. The result from the model is shown in Figure 41 and reflects this expectation: all patient types, regardless of location or priority, experience a very short wait time for their first appointment. The result can be interpreted such that the pooled network of four locations should be able to accommodate the demand of all four locations. Patients experience almost no wait time for their first appointment when the network is pooled. This policy also stabilized the system. In other words, the total supply of appointments now exceeds the demand for appointments and the wait times are no longer increasing without limit.

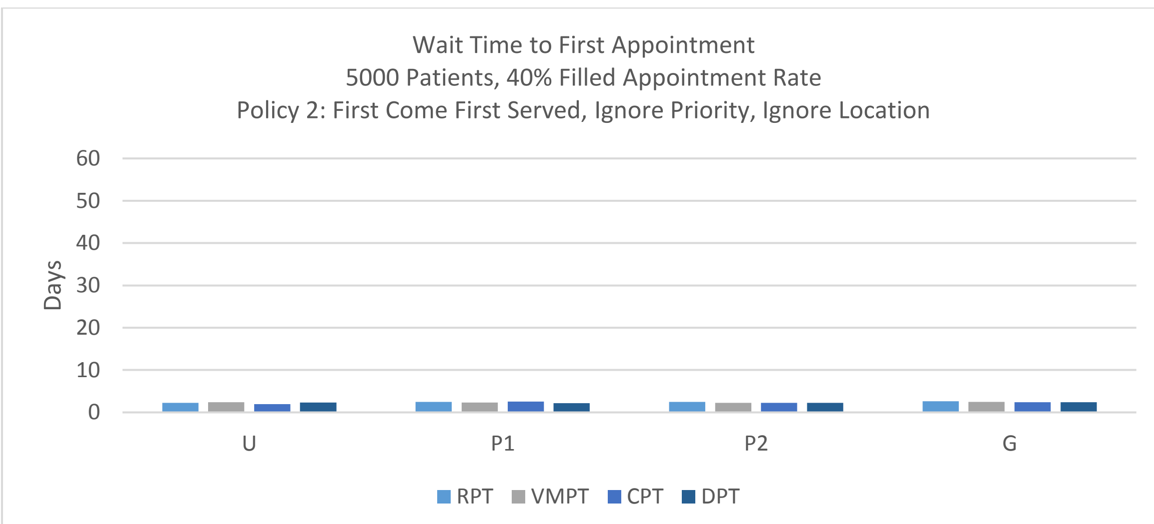

Figure 41: Average wait time to first appointment for all locations and all priorities, Policy 2

For comparison, the average wait time to first appointments calculated in Experiment 2 using the current state scheduling (Policy 3), are shown in Figure 42. The figure is shown to compare the steady state achieved using Policy 2 to the long wait times experience in Policy 3, the base case. CPT and DPT experience long wait times in Policy 3 while they experience almost no wait time in Policy 2. RPT and VMPT experience almost no wait time in either Policy.

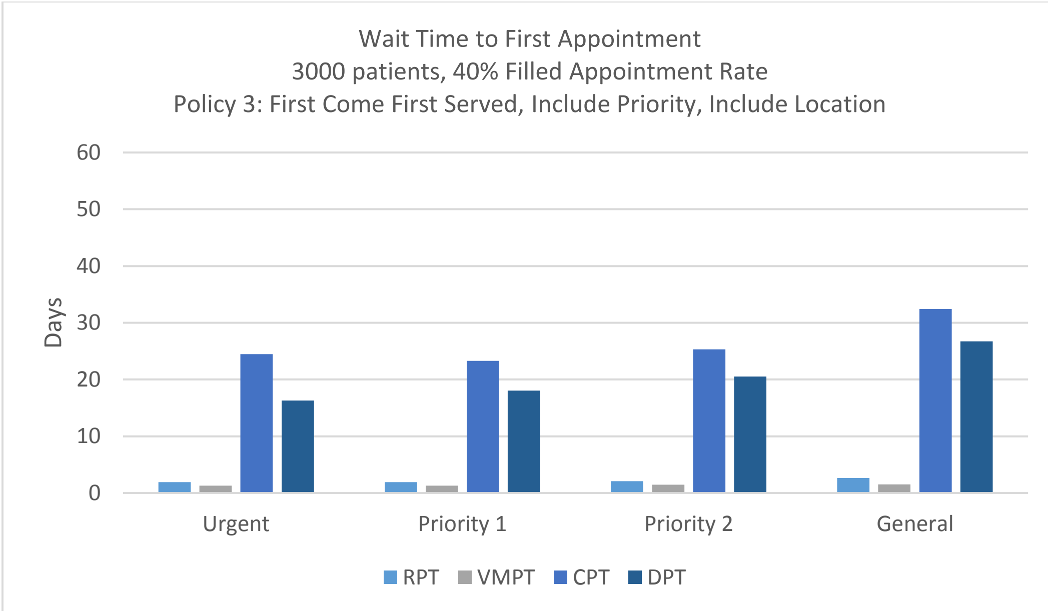

Figure 42: Average wait time to first appointment for all locations and all priorities, Policy 3

Policy 3 (Base Case)

Policy 3 represents the current queueing discipline and scheduling system utilized. Highest priority patients are seen first, in order of arrival. Patients can only be seen at their home location. The expected result of this policy is that higher priority patients experience shorter wait times, wait times are dependent on location, and wait times for locations with greater demand than supply have higher wait times. It is expected that the resulting wait times for Policy 3 are within the same range as historical wait times but it is not expected that they would be exactly the same because, as described in Chapter 6, Policy 3 does not reach a steady state because there is a shortage of supply at the CPT and DPT locations. Figure 43 shows a time series of the wait times to first appointment for General patients at CPT and DPT.

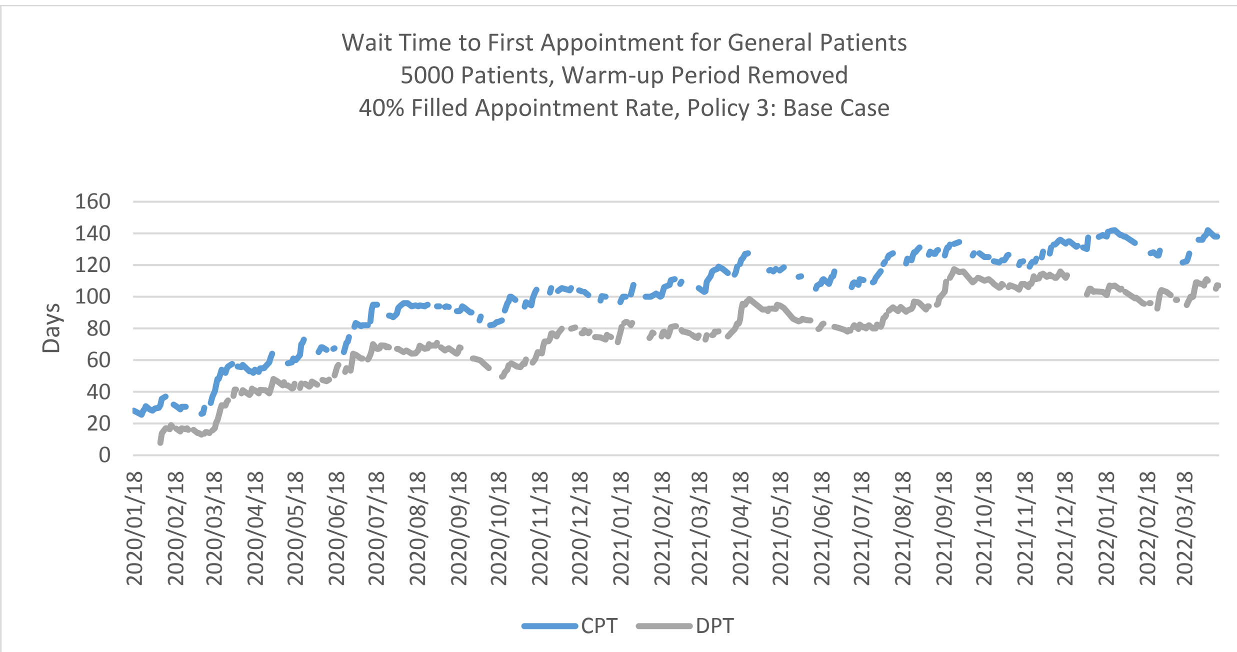

Figure 43: Average wait time to first appointment for General patients at CPT and DPT

Policy 4

Policy 4 represents the queueing discipline where patients are seen in order of Priority then First Come First Served, but their home locations are ignored. This policy ensures higher priority patients are seen sooner than low priority patients and that patients of equal priority are seen in order of arrival. The expected result of utilizing this policy is that patients of lowest priority should have the longest wait times, and that wait times are not dependent on location. The results of the model affirm these expectations and are shown in Figure 44. Slight fluctuations in wait times are likely due to differing sample sizes. Practically speaking, this policy generates very low wait times for all patient types. This policy also stabilizes the system and the wait times are no longer increasing without limit. The drawback is that high priority patients, including patients that have just undergone total knee or hip arthroplasty, may have to travel for their appointment.

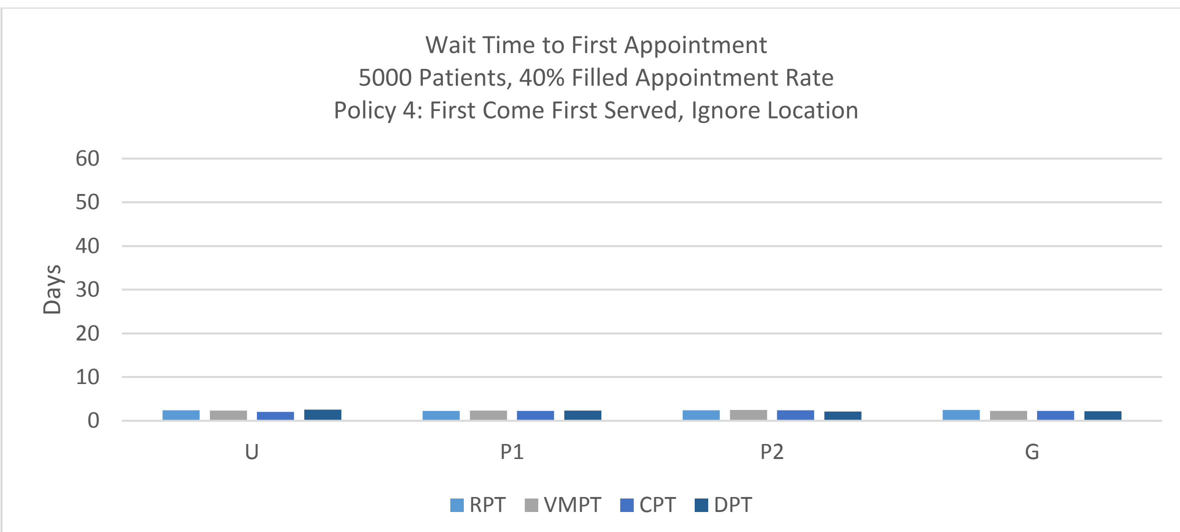

Figure 44: Average wait time to first appointment for all locations and all priorities, Policy 4

Policy 5

Policy 5 represents the queueing discipline that management is actually interested in implementing. High priority patients (Urgent and Priority 1) are seen at their home location. The practical reason for this is that these patients may have just undergone surgery and may have a more difficult time traveling for their appointment. These patients are the sickest and have the greatest need for physiotherapy. Management feels that these patients should be seen at their home location, but that lower priority patients should travel to a different hospital if there is a shorter wait time. The anticipated result of implementing this queueing discipline is that patients should have low wait times regardless of their location or priority, while still keeping high priority patients at their home hospital. Figure 45 displays the results, which show that the network still has enough capacity to support the demand, even if Urgent and Priority 1 patients are seen at their home location. This policy also stabilizes the system and the wait times are no longer increasing without limit.

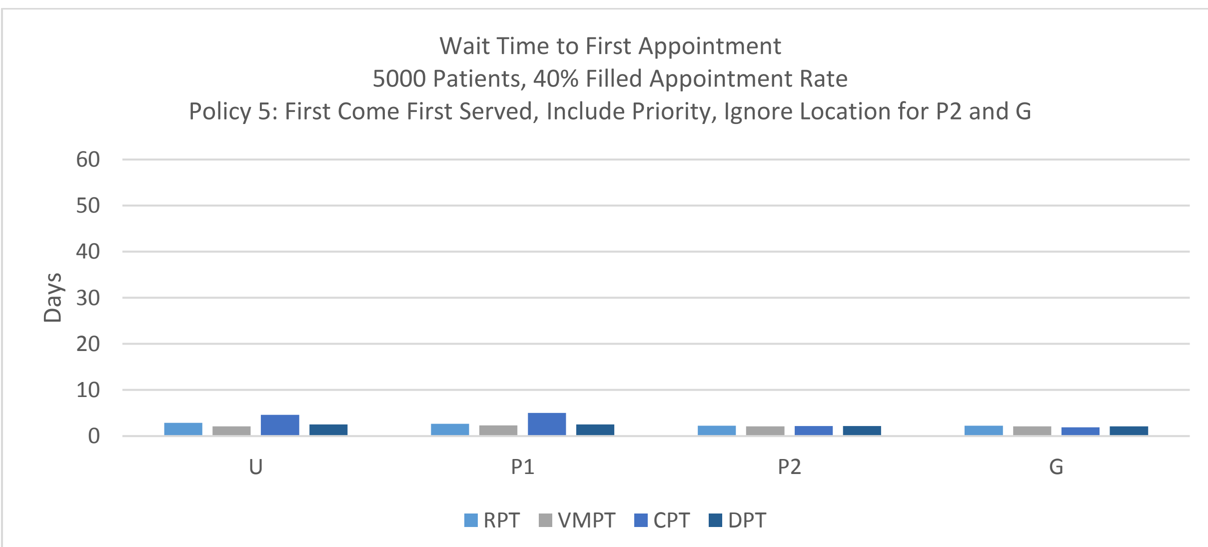

Figure 45: Average wait time to first appointment for all locations and all priorities, Policy 5

Increased Appointment Utilization

The model allows the user to understand the impact of increasing the number of filled appointments on wait times. This could be accomplished in several ways including the following examples:

- Reducing no-show and cancellations
- Increasing scheduling efficiency, e.g. using a cancellation list to fill an unused slot
- Increasing the amount of time clinicians dedicate to patient care

All of these scenarios are analyzed in the same way in the model: by increased the filled appointment rate. Figure 46 shows the average wait times for each type of patient at each location using a 50% filled appointment rate rather than a 40% filled appointment rate. The base case scheduling policy, Policy 3, is still used. The average General patient is seen within 7 days at CPT and DPT and the system reaches a stable state.

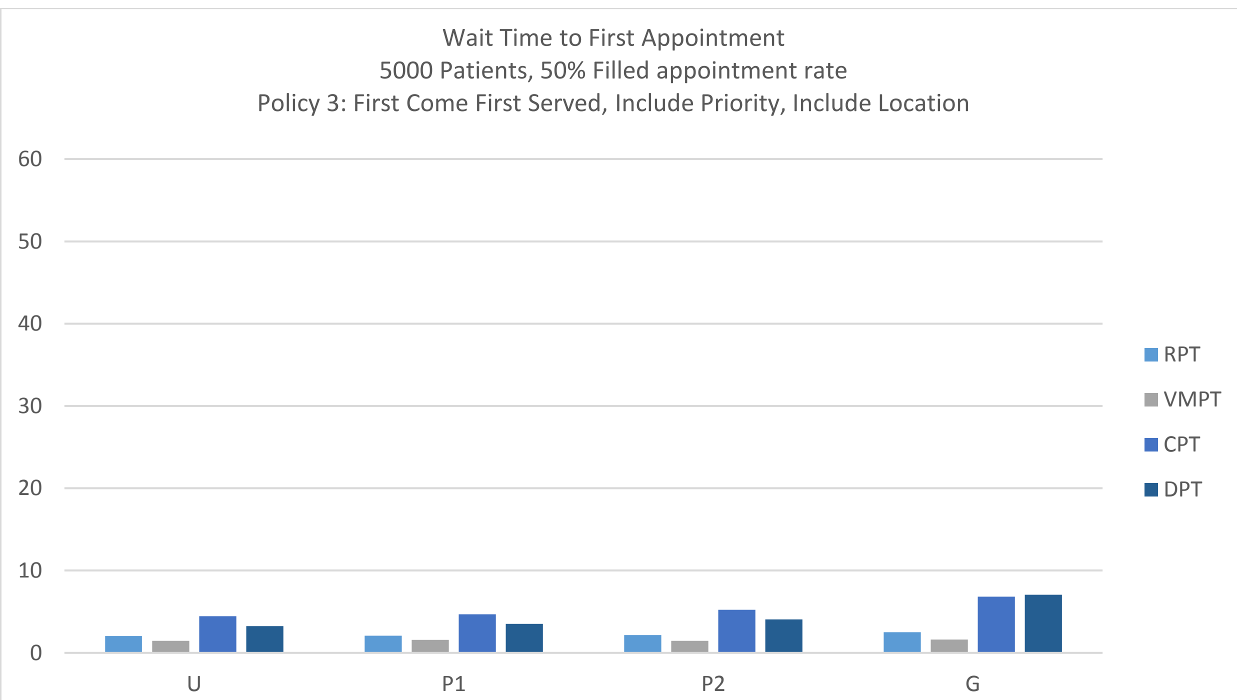

Figure 46: Average wait time to first appointment, 40% Filled Appointment Rate, Policy 3

Summary of Results

Table 14 shows a summary of the results and whether the scenario allowed the network to achieve steady state. Policies 2, 4 and 5 stabilize the network but only Policy 5 is actually being considered by management. Increasing the filled appointment rate also stabilizes the network.

Table 14: Summary of results

Scenario	Filled Appointment Rate	Description	Result
Scheduling Policy 1	40%	Ignore Priority, Include Location	Wait times grow without bounds for all priorities at CPT and DPT
Scheduling Policy 2	40%	Ignore Priority, Ignore Location	Wait times reach steady state for all locations and priorities
Scheduling Policy 3	40%	Include Priority, Include Location (Base Case)	Wait times grow without bounds for low priority patients at CPT and DPT
Scheduling Policy 4	40%	Include Priority, Ignore Location	Wait times reach steady state for all locations and priorities
Scheduling Policy 5	40%	Include Priority, Ignore Location for P2 and General	Wait times reach steady state for all locations and priorities
Increased Filled Appointment Rate	50%	Include Priority, Include Location (Base Case)	Wait times reach steady state for all locations and priorities

Chapter 8: Discussion and Future Work

The experiments conducted and analysis of results confirmed that the network of clinics does have ample capacity to serve the pooled demand if it fills 50% of its total available appointments. This result implies that clinics could improve their wait times either by reducing no-show rates, increasing direct patient time, or scheduling more efficiently e.g. filling more short-notice available appointments. A discussion with management revealed past attempts to improve no-show rates including attendance policies and appointment reminders. Unfortunately, the appointment reminder system is expensive and is not cost-effective for outpatient physiotherapy because it requires appointments to be loaded in the system more than two weeks prior to their date. It is effective for programs with longer scheduling horizons, e.g. Diagnostic Imaging.

Model Limitations

There are several limitations of the model that should be considered while interpreting results. The first is that the model does not accurately represent the entire scope of the referral and scheduling process. There are real-life delays throughout the schedule and referral process that were not studied during this work and are not represented in the model. The model instantly places patients on the wait list as soon as they require an appointment. In real life, patients sometimes must navigate the intake process and experience delays during it, sometimes referred to as Wait 0.

This transient behavior made it difficult to validate the current state model because wait times increased without bounds and did not reach a steady state. While in the past wait times may have hovered around some mean, it is not reasonable to try and validate the behavior of the model against historical wait times because there are many real-life reasons why wait times would remain steady whereas in the model they would not. Employees are human and may intervene to see more patients if they notice the wait times are increasing from the norm. Managers may choose to hold less meetings so that clinical employees can focus on patient care. Research and process improvement initiatives may be halted to allow for more time for patient care. Wait time blitzes or other times of increases in resources may be held to mitigate growing wait lists. We do not have information about any interventions that took place to maintain steady wait times in the past but we conclude that it is not reasonable to expect model wait times to reach a steady state around the mean historical wait time.

Another limitation of the model is that it fails to account for patient behavior while they choose their next appointment. In the model, patients are given the soonest available appointment and have no opportunity to choose a more convenient one. In reality, patients may decline the soonest appointment and wait for one that better fits their schedule. We would expect that the model would generate wait times that are shorter than actual historical wait times because it fails to account for this behavior. There are many reasons why a patient would not choose to attend the earliest available appointment but none of these are reflected in the model.

Appointment Attendance

Hospital outpatient services often experience high rates of no-show and cancellations. This topic was reviewed in Chapter 2. While some no-shows and cancellations are inevitable, managers and clinics should strive to reduce these rates because greater appointment attendance rates result in improved clinic efficiency and reduced wait times. Management recognizes this and have already attempted to reduce no-show and cancellations rates through various initiatives. This is important to mention because it provides context for why the focus of this work was not to reduce no-show rates, but rather to explore the use of different scheduling policies to reduce wait times to first appointment.

An obvious area for improvement at every clinic is appointment attendance. While it was known from the beginning that no-show rates were high, reducing these rates was not the focus of the project. No-show and cancellation rates have severe impacts on the flow, efficiency, and through-put of a clinic. They can also lead to increased waiting times and reduced patient outcomes. Recent technological developments have allowed for appointment reminder systems that are more modern and better aligned with today's patients. Examples of these systems include automated text reminders and mandatory online patient appointment confirmation. Similar initiatives to increase appointment attendance are underway in other outpatient services at the NSHA, for example in Mental Health and Addictions.

Risks of Sending Patients to Another Location

There are risks associated with sending patients to another location. As described by Beukers and Kemp, some patients will value having a shorter distance to travel for their appointment rather than experiencing a shorter waiting time (Beukers & Kemp, 2014). It is possible that sending patients to a different location than their origin location could negatively impact appointment attendance rates. Patients attending publicly funded outpatient physiotherapy likely do not have employer insurance to attend private clinics. While an analysis of patient demographics is outside the scope of this work, it is reasonable to infer that patients attending hospital outpatient physiotherapy may have a lower economic status than those attended private services. Patients may need to use public transit or other complicated means to get to their appointment. The effects of high no-show and cancellation rates on the health care system are severe, as described by (Kheirkhah, Feng, Travis, & Shahriar, 2016). Serious consideration should be taken to understand the risks of raising the appointment no-show rate before implementing a policy that requires patients to travel to a different location than their origin hospital.

Future Work

Recent work was undertaken at the VMPT location to refine the design of the schedule. This work involved staggering New appointments throughout the day to make them more accessible for patients as well as increasing the number of New appointments to ensure that each physiotherapist saw the same number of New patients per week. This type of job planning is effective because it increases fairness amongst clinicians and keeps the clinic accountable to offer a certain number of new appointments each week. Prior to this project, there was a belief amongst management that the number of return appointments and days in between return appointments was not standardized amongst clinics. The data analysis for this project confirmed that prediction. Management believes that offering more New appointments would better serve the population because it would allow patients to be seen sooner, reducing wait times, and improving outcomes. It is possible that further refining the schedule for each location in the Central Zone, focusing on offering more New appointments, could change clinical practices of retaining chronic patients for long periods of time and seeing more new patients. While it is desirable to offer more New appointments because it allows patients to be removed from the wait list sooner, the impact on Return appointments must be quantified. The offering of more New appointments could lessen the ability of the network to handle its demand for Return appointments, thus creating a new problem. The next step in this work could be to optimize the appointment schedule.

Other future research opportunities include exploring the impacts of implementing more complex scheduling policies, such as increasing priority policies. In an increasing priority queueing system, patients accumulate priority points as they wait. The result is that low priority patients who have waited a long time may be served sooner than higher priority patients who have just joined the waiting list. While this policy is interesting and arguably equitable, it would be difficult to implement. The operational burden of maintaining the wait list may result in the need for extra clerical wait lists. Further, staff may be resistant to low priority patients being seen sooner than high priority patients, even if they have waited a long time.

A final research opportunity would be to explore the impacts of a dynamic scheduling system, meaning that the system would respond to an influx of demand for new appointments by either temporarily increasing resources or adjusting the appointment mix to offer more new appointments. An important consideration would be to measure the detriment to the wait time for return appointments when adjusting the appointment mix to favor more new appointments. The mix of new and return appointments has been the topic of other projects at the NSHA, including in Mental Health and Addictions. A mitigating strategy for return appointment would be to implement maximum treatment lengths and standard time in between return appointments. This strategy would reduce the access to services for chronic patients who require continual service to the benefit of new patients who would be seen quicker. Rather than implementing a maximum number of return appointments, a mandatory re-assessment could be implemented, mandating a second clinical assessment to determine whether additional follow-up appointments would provide any benefit to the patient.

Chapter 9: Conclusion

The focus of this thesis was to reduce waiting time for low priority outpatient physiotherapy patients in the Central Zone of the Nova Scotia Health Authority. NSHA management was interested in understanding the impact of sending low priority patients to other locations in the zone to reduce their waiting time, effectively a partial pooling of resources.

The main tangible contribution is a simulation model that allows the user to quantify the impacts of utilizing different scheduling policies and appointment mixes. The user can modify the queueing discipline, the scheduling policy, the number of appointments, the appointment mix, or the no-show rate to test how the system responds. The scheduling policies were proposed by management and they were involved throughout the lifecycle of the project. The model was built in excel using VBA programming to ensure widespread use and access.

The results of the simulation suggest that the network of four locations has enough capacity to handle the demand for new appointments and that pooling resources for Priority 2 and General patients, by sending those patients around the network, would result in shorter wait times to first appointment and a stable system. These wait times could also be reduced by increasing the number of filled appointments. The wait times could actually be almost entirely alleviated (and the system stabilized) by increasing the number of filled appointments without having to implement a new scheduling policy.

Another tangible contribution to NSHA management is the descriptive statistics portion of this thesis. While wait time for return appointments was not the targeted measure for improvement, it was important to understand the clinical practices regarding return appointments and the differences between locations. Specifically, the information regarding the differences in number of return appointments and time in between return appointments between locations helps management to understand the differences in clinical practices.

There were also some intangible contributions from this thesis. This work allowed management to have a broader look at the flow of patients and scheduling in the whole zone. This type of strategy level work can be difficult to prioritize while focusing on the operational management of a program. Completing this work showcased how industrial engineering and operations research methods can allow decision makers to understand the impacts of their decisions before they make them.

The model is structured in a way that allows it to be configured for any outpatient scheduling system. Any program could enter information about their resources and appointments and use the model to inform decision making. It would be especially helpful in programs where patients have multiple visits, new visits are different from return visits, and return appointments are scheduled in batches. At the NSHA, good examples are Mental Health and Addictions and other rehabilitative services such as Occupational Therapy. The model will lead to more effective decision making and management being better informed about the outcomes of their decisions.

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