ESTIMATING THE IMPACT OF STAFFING AND CLINICAL DECISIONS ON WAIT TIMES FOR CHILD AND ADOLESCENT MENTAL HEALTH SERVICES

by

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Abstract

Background: The Choice and Partnership Approach was recently implemented at the three IWK Community Mental Health and Addictions outpatient community clinics in part to manage increasing demand on services. Positive results have been reported in past literature but questions remained about system flexibility and factors to maintain timely access to care.
Objective: To measure the relative contributions that various system factors have on increasing wait times.
Methods: Discrete event simulation was used to model the study clinic and modify system factors. Analysis examined the relative differences in wait times and the percent of clients that attained wait time benchmarks associated with changing system factors.
Results: Number of Partnership appointments, and the percent of clients continuing to Partnership session had the largest impact on increasing wait times.
Conclusions: Specific system factors may be overlooked when attempting to mitigate increases in wait times, but day-to-day processes have a significant impact on system level outcomes.

List of Abbreviations Used

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CAPA	Choice and Partnership Approach
CMHA	Community Mental Health and Addictions
CWS	Community Wide Scheduling
DES	Discrete Event Simulation
FTE	Full Time Equivalent
IAT	Inter-Arrival Time
IWK	Izaak Walton Killam
NS	Nova Scotia
PS	Partnership
VBA	Visual Basic for Applications

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I am excited for what's to come, and throwing myself at it with the same interest used to finish this thesis. I'm coming up for air, but only to take a breath and dive deeper.

Chapter 1: Introduction

1.1 Background

Nova Scotia's Government has identified child and adolescent mental health and addictions services as a priority area and recommends immediate action be undertaken to ensure timely access to care [1]. One in five Canadian children and adolescents experience symptoms that are clinically significant enough to warrant a diagnosis of mental illness, yet fewer than 25% of these people receive specialized care [2]. Nova Scotia has the highest rates of mental health care use across all ages, when compared to other Canadian provinces, in addition to higher reported rates of mood disorders, anxiety, and suicidal ideations or attempts [3, 4, 5]

The poor health, education, and occupational outcomes for people with mental illness may be compounded by delays in identification and treatment. It has been demonstrated that timely access to mental health care is important for successful treatment, and longer wait times may negatively affect long term outcomes [6]. In the short term, longer waiting times can affect the engagement with clinicians, with clients less likely to attend appointments as waiting times increase [7, 8]. In 2010, in response to 20-month long wait times for services, a number of Community Mental Health and Addictions (CMHA) clinics adopted a model of service delivery that would, among other benefits, support more timely access to care and thus would maximize the outcomes of mental health care for children and youth. The Choice and Partnership Approach (CAPA) model was designated as the new approach.

CAPA is designed to be a model of care that can respond to the needs of clients and families and is adaptable in how it is delivered. As a way to respond to increases in wait times, a system must accommodate surges in the demand for services, and changes to staffing levels to maintain adequate access to care. It is inefficient and impractical to simply increase personnel within a system to meet demand when surges occur; rather, systems should aim to be adaptive to surges in demand, and flexible with their resources. Intelligent human health resource planning can aid in the reduction of wait times, optimize client outcomes, and is a key component of the CAPA model [9, 10].

1.2 Overview of the Choice and Partnership Approach

The CAPA model is a service transformation approach that prioritizes client centred care and shared decision making between clinicians, clients and their families [11]. The processes of the model are intended to support shared decision making, goal-based outcome measurement, and maximize value-added care through principles of Lean, which focuses on waste reduction and efficient resource utilization. The operational components of the approach draw on concepts from queuing theory and demand-capacity methodologies to improve the capacity of the system to respond to client needs in an efficient and timely manner.

CAPA comprises 11 key components: Leadership, Language, Handle Demand, Job Plans, Team Away Days, Goal Setting, Selecting Clinician, Full Booking to Partnership, Choice Framework, Core and Specific Work, and Peer Group Discussion [12]. The first component, Leadership, articulates the purposes for which managers, clinician leaders, and administrators are to be engaged in planning and delivering mental health services. The language of CAPA was strategically chosen to support the shift in the philosophy of care from the traditional model of an expert with power to that of facilitator or partner with expertise. CAPA handles demand by tailoring services to local circumstances and needs, developing job plans for each team member's role accordingly, and supplementing these processes with focused days of full staff meeting, termed 'Team Away Days', to provide focused time together as a team to build trust and transparency in change-processes, and to support education and training.

Clients' and families' first appointment in a system using CAPA is called a Choice appointment which embodies many of the elements attached to its philosophical stance. These include engaging the client and family with the clinicians in co-formulation of the problem, goal Setting to articulate measurable and achievable treatment goals, and an associated plan for reaching those goals. Clients and families leave a Choice appointment with a shared decision about next steps and an identification of things they can do to help themselves right away. Selecting clinician means clients and families are matched to clinicians with competencies relevant to their goals of treatment, and full booking to Partnership means utilizing an open clinic booking system to allow clients/families to leave Choice appointments with a booked Core Partnership appointment if they require that level of intervention. A range of intensities and complexities of interventions are offered through Core (the majority of service delivery time investment) and Specific Partnership work (treatments that are of a longer or shorter duration or require unique skill sets) flows. Peer group discussion within small multidisciplinary clinical groups enables active discussion of ongoing work, and how to transition families into alternate levels of care, which includes supports for in self-management going forward ("letting go") [12].

1.3 The CAPA Model at the IWK Health Centre

The IWK Health Centre is a pediatric health centre which provides mental health and addictions services to children and adolescents aged 0-18 years within the Halifax Regional Municipality and provincially. As part of the services, there are three CMHA clinics located in Dartmouth, Sackville, and Halifax. Each clinic has unique levels of demand and were not modelled as one process. Thus only one clinic was selected as the study clinic, and data was collected for this clinic.

To understand the operation of CAPA, it is helpful to understand the basic CAPA flow, the Choice-to-Core-Partnership flow, as it will apply to this project and will be conceptualized throughout the research, as visualized in Figure 1.1.

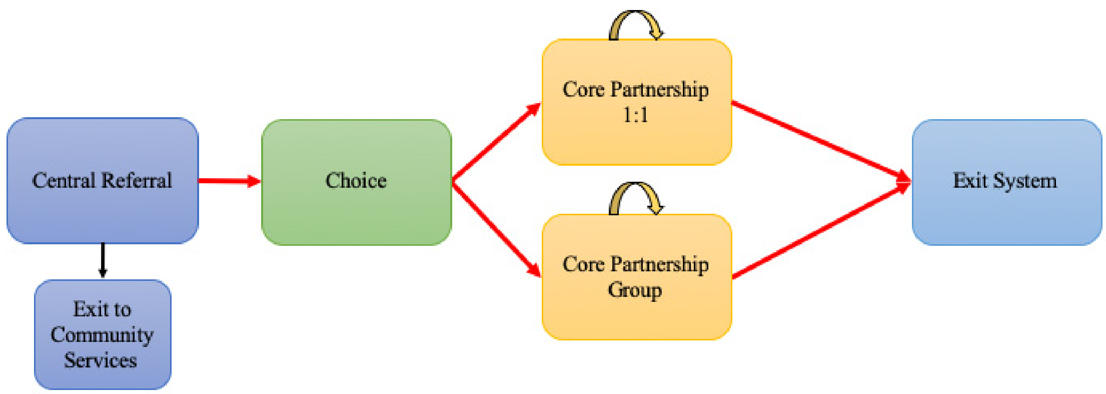

Figure 1.1: Conceptual flow of clients in the flow of Choice-to-Core-Partnership services using CAPA Processes

Entry into the CMHA system begins as contact with the Central Referral team, which assesses the child's/adolescent's mental health care needs over the phone. Through the Central Referral process, the client is referred to the setting best suited to their stated mental health needs, which may be emergency/urgent care, primary care or community supports, services either within or outside of formal health services, or tertiary level care with a Choice appointment within an outpatient team setting.

The Choice appointment moves away from a routine full assessment for all new clients, as used in the past, and, while including an assessment lens, narrows focus on the presenting concerns and goals described by clients and their families [11]. During this appointment, decisions about next steps in treatment are guided by the client and the family goal discussion to determine if the client will continue with the CMHA services, match to community supports, or exit the formal system to self-manage. If, at the end of the Choice appointment, a subsequent mental health intervention session is booked, then a match is found with a clinician or service to best attain the goals discussed, which are worked on in the subsequent Partnership appointment(s). If the family and clinician are unable to reach a decision at the end of the Choice because of lack of agreement or due to not having the necessary people in the room to inform decision-making, the family may return for a "Choice Plus" to continue the appointment to reach a conclusion about the treatment plan.

Partnership appointments can be further divided into two levels, Core or Specific. Most clients participate in treatment through Core Partnership, which consists of common mental health treatments delivered in individual or group settings, including Cognitive Behavioural Therapy or Acceptance and Commitment Therapy. In the event that a client in Core Partnership requires augmentation with further or a different type treatment, Specific Partnership can provide more specialized services, such as medication prescriptions or treatment, that require a shorter or longer duration than typical [6, 11]. These Specific Partnership appointments help ensure clients receive the appropriate level of services, and maximize flow through the system, thus preventing siloed services that may result in backlogs or waits. Additionally, the Core stream of services often meets the needs of the majority of clients coming into the services. Within CMHA, some Core Partnerships are offered within a group setting, which is clinically useful for clients with similar problems, like anxiety, and is an evidence-based practice that can maximize the use of clinician time. At any time in treatment, a client may leave services for reasons such as reaching treatment goals, mutual agreement, loss to follow up from non-attendance, or transfer to other services.

Core Partnership appointments comprise the majority of appointments at IWK CMHA clinics; therefore, factors affecting these processes have the greatest potential for reduction of time waiting for appointments. As such, process experts in the study clinic identified the Choice-to-Core-Partnership Pathway as their priority area for identifying effective strategies for supporting client flow.

1.4 Supporting Operational Decision Making

CAPA has had promising results within the IWK CMHA, since its implementation across all clinics. A recent study reported that within the IWK CMHA, CAPA has resulted in a decrease of wait to an initial Choice appointment from 225 days in 2011 to 93 days in

2013 and 28 days in November 2019. However, there was an increase in wait to subsequent Partnership appointments from 59 days to 96 days from 2011 to 2013, but a decrease in maximum wait of 57 days by November 2019 [11]. Although the reported overall (sum of referral to Choice wait, and Choice to Partnership wait) decrease in wait times is a promising outcome from the implementation of CAPA, there was concern surrounding the long-term increase of wait times between Partnership appointments. There are also challenges raised by content experts about the sensitivity of the system to increases in wait times due to staffing changes (e.g., due to attrition or to replace leaves) and fluctuations in demand for services as a result of either increases in numbers of young people presenting for Choice appointments or continuing on to Partnership, whether due to changes in population needs or in response to lack of availability of alternative services. Following Birch's framework of Health Human Resources Planning, this project aimed to support operational decision making within a CAPA-based service to ensure "...having the right skills in the right place at the right time to provide the right services to the right people" [9].

Given the questions pertaining to CAPA's function with changes in staffing and demand, there was interest to understand factors impacting the system. To properly plan within a healthcare system, it is important to identify opportunities that introduce resource flexibility, or potential variations in resources that may limit increases of wait times [9]. Based on the consultation with CAPA content experts, several areas have been identified as system factors that could be changed to increase the system's ability to manage higher demands.

CAPA process experts have identified three scenarios that may contribute to increases in wait times that warrant study to inform effective service planning strategies: 1) increases in youth presenting to mental health services; 2) changes in staffing configurations and numbers; and 3) the number of sessions that a client completes before a formal exit from the system. Without tools to do so, it is difficult to quantify the relative individual impact each of these would have on wait times, and even more challenging to communicate the potential changes they have in a system. The quantification of the relative effects is best understood from the perspective of complexity science and its role in health systems.

1.5 Complexity Science in Health Services Research

Complexity science is a concept that works to explain and understand how systems are connected and explain the interactions arising from these connections [13]. Recent scoping reviews have found that the application of complexity science to health systems is a relatively new concept, with some studies emerging around the late 1990s, and a marked uptake in literature shortly after this time [14]. Complex systems are characterized by non-linear interactions, feedback loops, interaction with the surrounding environment, and dynamic states [15]. A key concept in complexity science is to understand a system, not as the individual components, but rather as the relationships and connections between these components [15].

The understanding of these complex and non-linear interactions is extremely difficult, yet in order to be responsive to changes, attempts must be made to plan within health services and adapt to shifting needs of a population or changes in resources. The impracticability of experimentation with system-level changes make it difficult to anticipate the outcomes of an intervention in a complex systems. In order to understand the impacts that system factors may have on wait times, there exist tools to portray and experiment with factors of complex systems. To help understand complex systems the use of simulation tools is becoming more common in the healthcare context, with promising opportunities to improve communication of findings [16, 17]

Simulation models are abstractions of these complex health systems and can help us understand the relationships between system components, sometimes resulting in unintuitive relationships otherwise hidden from traditional statistical methods [18]. A simulation approach to systems thinking can provide quantitative evidence for a policy level decision, and a means of gaining insight into the drivers of problems. Moreover, the results from a simulation model can be communicated in a way that is clear and informative, without the need to describe the entire system in depth[19, 20, 21]. Concise and efficient answers to problems are crucial to help support services planning and communicate to those from other disciplines or backgrounds.

Within CMHA services, process experts identified the Choice-to-Core-Partnership Pathway as the priority area for identifying effective strategies for supporting client flow. We modelled an element of the Choice-to-Core-Partnership Pathway, namely the common flow within core treatment delivery of CAPA. This consists of an initial Choice appointment, continuing to Partnership appointments, engaging in a number of these appointments, (CAPA states the average is typically 7 to 8 per client) and a formal system exit upon goal attainment or other reasons [12]. For our purposes, the Choice-to-Core-Partnership Pathway assumed equal levels of urgency, with priority appointments not being included.

Chapter 2: Objectives

The overarching question addressed by this thesis is: What staffing strategies are likely to maintain the provincial wait times benchmarks (28 days for Choice, and 14 days for first Partnership) within IWK Child and Adolescent CMHA Services? We aimed to quantify the relative impact different system inputs have on wait times, through changes in:

1. Fluctuations in demand for services as captured by demand for Core Partnership appointments

2. The number of available personnel resources and staffing configuration determined by full-time equivalents (FTEs) and distributing workloads

3. Number of Partnership appointments as measured by average numbers in sessions and rates of no-show to booked appointments

Chapter 3: Methodology and Design

3.1 Overview

We employed a Discrete Event Simulation (DES) to model the potential relative impact of fluctuations in demand for services, staffing complement and configuration, and mean number of client sessions on wait time measures. CAPA is a flow-oriented process built on Lean principles of minimizing waste and increasing value added care to maximize resource efficiency. A simulation modelling approach is appropriate for studying the effects of changes to demand for resources on wait times, while considering the stochasticity of the system under study.

DES is a tool developed out of the disciplines of Operations Research and Industrial Engineering, used to understand and test complex systems. DES focusses on queues, resource utilization, and entities (mental health services clients) for this research. This method suits the research as we are interested in the wait times of individuals, and the utilization of clinicians for each stage of the CAPA model. Our research questions do not require representation of feedback systems or require capture of the often-complex interactive behaviour of humans, and, as such, have not taken system dynamics or agent-based modelling approaches. The goal of the model is to create a simulated cohort of people, populated with available data, or professional opinion when data are unavailable to represent the flow of clients through the Choice-to-Core-Partnership Pathway. The simulation is then replicated a number of times to collect information on system variation and stochasticity. It is important to include enough information in the model to capture the key aspects of the system likely to influence wait times, without incorporating too much complexity which would limit its effectiveness as a communication tool and increase data requirements.

The use of simulation in health services research is a fairly established tool that benefits from integration of health services researchers, merging their understanding of health contexts with formal DES methods [22, 23]. A simulation tool can be used for decision making, when there is trust in the methods and approaches, which is gained from early and routine engagement with process experts. Health systems are stochastic, and require methods that move away from static or deterministic analysis, in addition to methods that lend themselves to context-specific communication. Moreover, as complex questions continue to be asked of health services research, a systems approach to study is warranted. Creating and observing client flow, at a system level, can uncover complex, nonlinear relationships, and provide insight into system level interactions. DES provides a useful tool for addressing a complex research question and informing policy with computational experimentation and feasible solutions. Lastly, this thesis served as a 'proof-of-concept' for using simulation as a communication tool in this clinical setting.

There are multiple approaches to the application of DES, and the approach in this thesis was to create a stable, or steady-state, baseline representation of the Choice-to-Core-Partnership Pathway that was within targets for waits to a Choice appointment and waits to first Partnership. We then systematically added strain to the system by varying system factors (i.e., increased demand, decreased staff, or increased average number of Core Partnership appointments), meanwhile measuring the relative impacts of each system factor. This provided information about conditions that may have led to wait time increase, or that are not meeting benchmarks, as well as insights about the relative contribution that each system factor has on wait times.

3.2 Knowledge to Action Cycle

Effective communication between clinical content and modelling experts was necessary to ensure the simulation model accurately represented the main components of the Choice-to-Core-Partnership Pathway. The work was situated in the context of the Knowledge To Action Cycle as a guiding framework to inform effective Knowledge Translation, and integrated learning for both process experts and the research team [24, 25, 26]. The Knowledge To Action stages are: 1) Identifying the Knowledge To Action Gaps; 2)Adapting Knowledge to Local Contexts; 3) Assessing Barriers/Facilitators to Knowledge Use; 4) Selecting and

Implementing Interventions; 5) Monitoring Knowledge Use; 6) Evaluating Outcomes; and 7) Sustaining Knowledge Use. Stages four to seven of the Cycle did not apply to the scope of this thesis, but were used to guide other stages and remain useful for future work. The use of the Knowledge To Action Cycle allowed a common process to be followed and facilitated the crucial components of integrated Knowledge Translation.

Identifying knowledge to action gaps set the foundation for the research. The IWK CAPA Advanced Practice Lead was a member of the research team and was a natural liaison with other process experts (i.e., clinicians, industrial engineers, booking and registration clerks, decision support analysts) needed to inform the various stages of model development over the course of the project. The purpose of the research was to provide quantifiable answers to the information gaps identified by the process experts to audiences including clinicians, managers, clinical leaders, and the director. The nature of conceptual modelling and understanding the problem facilitates a natural progression from identifying gaps to adapting the knowledge to the local context.

The inclusion of a wide range of process experts supports opportunities to assess barriers and facilitators to knowledge use. A key consideration in the modelling approach was to ensure the ability to use collected data in a meaningful and accessible way. As such, process experts defined key outcome measures (wait times) and data sources to support the implementation of the tool in a meaningful and sustainable way to support decision making.

3.3 Input Data Sources

Two sources of data were identified by content experts for use for this study, scheduling data from the clinical scheduling system and job-planning data from the job planning system for the IWK CMHA clinic. The scheduling data were requested from the IWK Research, Evaluation, and Outcomes team, who extracted it from the clinical system Community Wide Scheduling (CWS), and also played a role as a process expert to describe the data and any assumptions it may make. CWS is software that collects routinely reported data from providers. This data source allows routine updates to the model, as more data are collected and extracted. These data provided information on numbers of Choice and Partnership appointments and rates of no-shows.

Two separate inclusion criteria were developed by the data custodian, clinic manager, and booking and registration clerk, to be applied for extracting Choice and Partnership appointments for the study clinic. The inclusion criteria for Choice appointments were all clients who had a non-urgent Choice appointment between April 1st, 2017 and March 31st, 2018. Partnership inclusion criteria were those who had a Choice appointment between April 1st 2017 to March 31st 2018, and subsequently had exclusively non-urgent, Core Partnership appointments. The differing inclusions were applied because all clients, regardless of treatment, undergo a Choice appointment, but we wanted to focus exclusively on non-urgent Choice and Partnership sessions. Of all appointments captured, there were 456 unique clients for Choice demand, with 384 (84%) having 100% Core non-urgent Partnership appointments. The data were used to provide baseline input parameters of demand for Choice, Partnership, and the number of Partnership sessions.

The second source of data came directly from a CMHA clinic and informed the team-based quarterly job-planning aspect of the model. These data are tracked with a spreadsheet that calculates time dedicated to each activity for each provider. The data within these spreadsheets provide historical configurations of the clinical staff's time and were used to understand how job planning was undertaken. Data include number of FTEs, time allocation to Core activities represented as "Blocks" of time), and distribution of Choice and Partnership appointments in a quarter.

This job-planning data represented another set of opportunities for integrated Knowledge Translation to ensure the data could be incorporated into the model, and would have the ability to be used on an ongoing basis. Process experts such as clinicians, industrial engineers, and clinic managers, contributed to discussions to ensure all steps of job planning were understood, and subsequently how job plans would be conceptualized in the final model. These meetings and consultations were key in developing a model that can be used as updated job-planning data becomes available, and for understanding all components.

These two data sources were used to create the baseline simulation inputs. Scheduling data and job-planning data act as model inputs and are not analyzed beyond gathering appropriate baseline input settings.

3.4 Data Analysis

The analysis for the research comprises two distinct components. First, based on data collected from the clinic, analysis was undertaken to populate the model input parameters. Upon generating the model input parameters, the simulation model factors were then varied and run to produce simulated output. Analysis of this simulated output is the second component of the research.

For the first stage of the analysis, the two input data sources provided data for descriptive statistics analysed using SAS Software v9.4, and input distributions were fit using R v3.4. [27, 28]. Upon fitting input distributions, model output distributions were tested using a X^2 goodness-of-fit test to ensure the distributions did not significantly differ. The results from the descriptive and distribution fitting were used to populate the baseline simulation with relevant inputs.

The input parameters from the first stage were used to generate a baseline scenario with wait times within benchmarks, which served as the comparator for our system factor experiments. The second stage of analysis was based on the model output as system factors were varied. These variations in system factors provided information about the relative contribution of each factor to increases in wait times, namely, 1) Wait to Choice Appointment; 2) Wait from Choice to First Partnership Appointment; and 3) Wait between subsequent Partnership Appointments. Along with wait times, we report the percentage of clients for whom the Choice wait benchmark of $\leq$28 days was met, and the first Partnership benchmark of $\leq$14 days. Simulation replicates are expected to follow a normal distribution as repeated measures of the same metrics are collected to provide a confidence interval around the output mean [29]. Given this assumption, t-tests were performed on continuous variables and differences in proportions, when comparing baseline to alternate system factor settings. The five system factors were:

1. Percent of clients that continue to Partnership appointments
2. Proportion of the demand for core skillsets among providers
3. The number of FTEs available to the clinic
4. Mean number of Partnership appointments per client
5. Percent of Partnership appointments that are no-shows

These five system parameters were selected to balance the needs of the study clinic, with the desire to better understand factors that influence wait times more generally. The clinic identified as the Partnership appointments as playing the largest role in the system, and therefore all system factors, with the exception of number of FTEs influence Partnership waits, and not Choice waits. In order to understand waits more generally, all system factors can be translated, more broadly, to other services, such as emergency departments, primary care, or specialist waits. In terms of system functioning, we varied the system's in-flow (clients continuing to choice), the length of treatment (number of appointments and rates of no-show), and the system's human resource capacity (number of FTEs and distribution of workload).

The range and gradation of variations for each system factor were determined with process experts to ensure experimental settings were within plausible bounds and could realistically be modified if required. The gradations of change for system factors variations were determined in order to capture the impact of smaller changes, meanwhile supporting the ability to realistically implement changes and communicate results. All of these system factors are ubiquitous across health systems and therefore add to our understanding factors impacting wait times more generally. Lastly, system factors were varied individually, as opposed to concurrently to measure the *relative contribution* of each factor to communicate the impact.

As a means to provide a sensitivity analysis of the individual contributions of each of the five system factors on wait times, we varied each factor in way that would increase wait times, in addition to variations that would decrease wait times. In order to decrease wait times we removed system strain of each factor, which included: fewer Partnership appointments, less demand for Partnership, and adding FTEs to the clinic. If the system factor could not be reduced plausibly or practically, we did not reduce system strain as expert opinion could not validate the results. We did not further decrease system strain with workload distribution, as the baseline scenario was even, or by reducing the rate of no-shows as the baseline scenario of 9% was already low compared to a typical mental health clinic. The baseline scenario was developed as a steady-state system, and therefore the removal of system strain should result in little reductions of wait times, as defined by deterministic equations, adding the ability to validate model functioning.

The analyses included the conceptualization of wait times in terms of human resource requirements to serve as a tool for translation of results, to associate the human resource requirements necessary to mitigate wait time increases resulting from varying system factors. The process for determining the additional FTEs required to prevent an increase was as follows:

1. Re-configure the simulation model with an individual system factor varied to increase system strain. This setting was selected such that it significantly increased wait times to Partnership, and determined by process experts as being of interest. For example, changing 6.5 appointments per client, to 7.5 was a better comparison for process experst, than say adding 0.5 appointments on average.
2. 0.5 additional FTEs were then set within the re-configured model.
3. The new configuration was run with the system factor and FTEs settings and the output was compared to the baseline configuration results
4. If the results from the new configuration matched the results from the baseline scenario, we had determined the number of additional FTEs required to mitigate an increase. Otherwise, we repeated steps 2-3, adding 0.5 FTEs until the results from the new configuration matched baseline results.

The number of FTEs required to counteract increases in wait times due to system factor variations, provided a second outcome measure in addition to wait times. The wait time to first Partnership was used to measure change from baseline, the system factors considered in this research would not have an impact on wait times for Choice. These results do not provide the required FTE to restore wait times to the baseline scenario, but rather the number to *pre-emptively* avoid an increase, given a change in the individual system factor.

Chapter 4: Model Formulation

4.1 Conceptual Model of CAPA

The conceptual flow of clients through the simulation model is shown in Figure 4.1. The flow has been colour-coded to show where outputs are measured (green circles), how a client can exit the system (red triangles), and at what stages a system factor can have an impact (outlined dashed boxes). When a system factor has an impact, the resulting outcomes will be transferred downstream in the system and are not isolated to one dashed-outlined process. As the conceptual model is described, processes that have system factor variations will be explained to understand where in the process variations are being made.

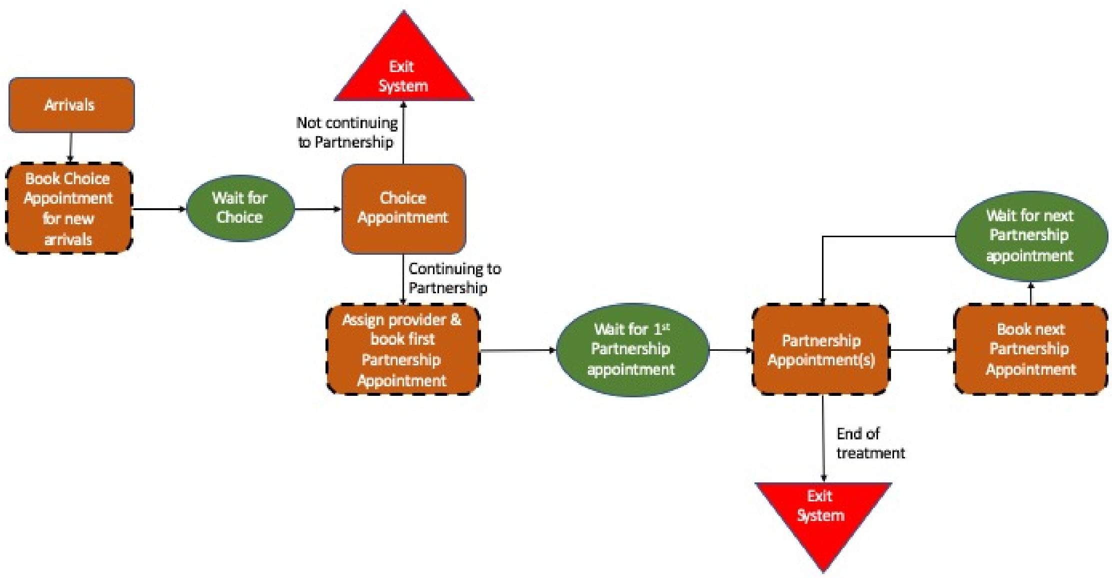

Figure 4.1: Conceptual flow of simulation model. Green circles represent outputs, red triangles show exit paths, and boxes with dashed outlines are steps that are impacted by the five system factors.

As a client arrives to the system from Central Referral, the first step is to book a Choice appointment, for all arrivals regardless of skillset preference or whether they will continue to Partnership sessions. The availability of a Choice appointment is affected by the system factor FTE amount, which is the only system factor considered in this research that impacts the model at this stage and therefore can have a substantial downstream impact. After booking and waiting for the Choice appointment, the client will undergo the appointment itself, non-attendance rates were not included for Choice Appointments as they were not identified as an issue at the clinic, and the assumption was 100% attendance. Upon completion of the Choice appointment, the client either exits the system if they are not continuing to Partnership appointments or are assigned a provider for Partnership appointments and booked for their appointment.

There are three system factors acting on both the Partnership provider assignment and the availability of the first Partnership appointment booking block - which occur simultaneously. The percent of clients continuing to Partnership sessions, the number of available FTEs, and the balance of demand for providers' skillsets all contribute to changes in wait times and FTE requirements downstream in the model. Upon having a provider assigned to the client, and booking the first Partnership appointment, a client will wait for the first Partnership appointment.

Both the mean numbers of sessions and the rate of no-shows for Partnership appointments influence the wait times to and between Partnership appointments and FTE requirements. These act on appointment process separately from the searching for an appointment, as the search is not associated with the length of treatment, and, in reality, the number of sessions is not known at the start Partnership sessions. Moving forward, the wait between Partnership sessions occurs after the first Partnership appointment and the client will cycle back to Partnership appointments until they exit the system. This was a deliberate decision as the Partnership processes comprise the majority of the system and have a large role in dictating the length of time a client spends in the system. Moreover, the clients' Choice appointments do not have individual clinicians assigned to them, but rather a group of clinicians that carry out the appointments, and thus largely act as a first-in-first-out approach to finding appointments.

By design, the Choice to Core Partnership pathway is meant to simplify and provide clarity to clients regarding the flow of the process, pulling additional resources when necessary based on client and family needs. The system factors selected for study have the greatest potential to influence this flow, and hence affect the experience for clients and families.

4.2 Model Inputs

4.2.1 Demand for Services

Numerous factors contribute to the overall demand for services within the model, with the first being number of calls to Central Referral that meet criteria for CMHA services, and will require a Choice appointment. Arrivals are represented in the model by the mean for the underlying distribution of booked Choice appointments for each day. The clinic dataset included 456 unique clients, represented the demand for Choice appointments over the course of a year, with the number of working days set to 240. There was a mean of 96 (86-106) clients booked to Choice in each quarter, with this value used as the daily arrival rate distribution, determined using log-likelihood estimation, Figure 4.2. Three discrete distributions were tested: 1) Poisson; 2) geometric; and 3) negative binomial. The negative binomial was determined to be the best fit using log-likelihood, AIC and BIC displayed in Table 4.1. The baseline negative binomial mean daily arrival rate was determined to be 1.6, with a size parameter of 2.69, as required to specify the Negative Binomial parameters. A goodness-of-fit test of the model output and input distribution showed no significant differences ($p < 0.001$).

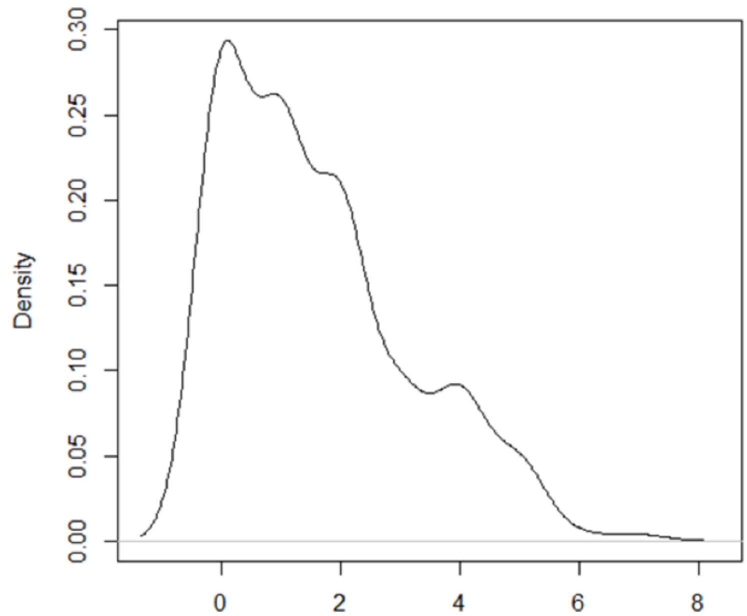

Figure 4.2: Density plot of daily arrivals for Choice

Table 4.1: Distribution fitting for daily arrival rate

Distribution	LogLL	AIC	BIC
Poisson	-418.27	838.55	842.03
Geometric	-415.76	833.52	836.99
Negative Binomial	-406.33	816.66	823.62

Subsequent to the Choice appointment, a number of clients will exit the system at this point and will not continue to Partnership sessions. As the baseline input, it was determined that 249 (65%) of the 384 clients continued to Partnership appointments, and the remaining 35% did not continue to have Core-partnership appointments. This is based on the number of clients who have a single Choice appointment, with no subsequent Partnership. Overall demand for Partnership appointments is represented by the percentage of the daily arrivals to Choice who continue to Partnership. Percentage of no-shows are calculated for each subsequent Partnership appointment (i.e., for first, second, third, etc. Partnership appointments).

The Partnership demand input was provided by the average number of Partnership appointments per client, which is determined by drawing a random variate from an input distribution. Upon analyzing input arrivals for Choice, the data were limited to those continuing to Core Partnership appointments, which did not include Specific Partnership or Group Partnership, representing 384 clients (84%) of the 456 in the data set. Given that the clients in the system now will all attend Partnership appointments, the rate of no-shows acts as another system factor that can have an impact on wait times. Cancellations of Partnership appointments were not identified as a problem in the clinic; thus, the assumption was they do not impact the number of sessions. Lastly, only clients with at least one attended appointment were used to determine the distribution of the number of Partnership appointments. Based on the clinic data for clients attending only Core Partnership services, the no-show rate was calculated to be 9.24% of appointments. It should be noted that the study clinic has an exceedingly low rate of no-shows to booked appointments in recent months, due to focused efforts by the booking and registration staff to follow-up with clients and remind them of appointments.

Similarly to Choice arrivals, the number of attended Partnership sessions provided by the clinic data set underwent distribution fitting for use as a model input, Figure 4.3. The same three discrete distributions were tested for the number of appointments: 1) Poisson; 2) geometric; and 3) negative binomial, using Log-likelihood, AIC, and BIC as the criteria of best fit. The number of sessions density plot is shown in Figure 4.3, in addition to the distribution fitting results in Table 4.2. It was determined that the negative binomial distribution was the best fit. The mean number of appointments for the baseline model was 6.5, with a size parameter of 2.12. The negative binomial best represented the 'long-course' clients that contribute to the 'tail' of the distribution. There was some interest in the ability to change the length of this 'tail' separately from the central distribution for the number of appointments. Ultimately this was not tested in the system factors, as the mean number of appointments captured an increase in the majority of clients.

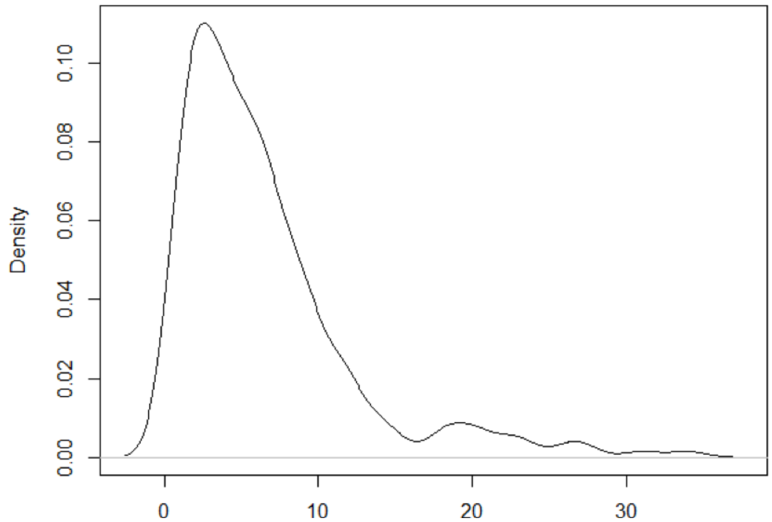

Figure 4.3: Density plot of number of sessions

Table 4.2: Distribution fitting for number sessions arrival rate

Distribution	**LogLL**	**AIC**	**BIC**
Poisson	-877.33	1756.66	1760.10
Geometric	-683.68	1369.37	1372.81
Negative Binomial	-663.30	1330.59	1337.49

4.2.2 Resource Capacity of Clinic

Before outlining the inputs for resource capacity, it is important to understand the "blocks" system CAPA uses to define time and distribute tasks throughout a clinical team. A clinician who is 1.0 FTE has 10 blocks of 3.75 hours to fill in one week, which is divided equally across weekdays to give 2 blocks per day. Of the 10 blocks, 40% of this time is dedicated to Core activities, the other 60% going towards Specific Partnership time, Group Partnership, administrative time, research, team-away days, and other essential staff duties. An appointment consumes half of a block; therefore, a 1.0 FTE has the capacity to provide eight Partnership appointments in one week. It is decided, during job-planning, how each clinician will divide their blocks – down to the half block - between Choice and Partnership, based on expected demand. Lastly, for every block of Partnership a provider lists, she/he may take on three new clients in a quarter.

The goal of the resource capacity input was to match the job planning process as closely as possible, without including extraneous information not pertinent to this model (such as time spent on research, administrative tasks, learning, etc). The outcome of the job-planning data, see Table 4.3, shows the FTE, Choice Blocks, and Partnership blocks over the time of the clinic data. Within the clinic, providers often extended over the 40% Core assumption, therefore the number of blocks were used to determine clinic capacity, as opposed to number of FTE. The average, over each quarter, was used to define the baseline model capacity, giving means of 5.5 Choice blocks, and 40.5 Partnership blocks, carried by 11.5 FTEs.

Table 4.3: FTE Data per Quarter and Model Input

	Q1	**Q2**	**Q3**	**Q4**	**Mean**	**Model**
FTE	13.8	14.1	13.1	11.5	13.1	11.5
Choice Blocks	5.0	6.5	6.0	5.0	5.6	5.5
PS Blocks	45.9	40.5	41.0	34.6	40.5	40.5

Once the blocks have been divided between Choice and Partnership for each provider, the job planning spreadsheet translates this into the number of weekly Choice and Partnership appointments available, and the maximum number of new clients a provider can take on in a quarter (3 times the number of Partnership blocks). These values are used to determine provider-specific availability throughout a week, for both Choice and Partnership appointments. Lastly, the preferred skillset required by a client places demand on specific providers and can create an increase in demand for a specific type of skillset or service. Skillsets were not defined by particular type; rather, this input was conceptualized as the percentage of clients that would require a specific skillset, with the number of skillsets, number of providers per skillset, and the percentage of demand for a skillset being modifiable within the model parameters. The only limit on number of skillsets is that it must not exceed the number of clinicians, which permits each clinician to have their own skillset.

4.3 Baseline Scenario Configuration

The baseline scenario was determined through the analysis of clinic data, in addition to professional opinion to confirm any input without available data. The results from the data sources dictated the input parameters used to create the baseline scenario. Table 4.4 summarizes the input values generated from the various data sources.

Table 4.4: Values used in the baseline scenario

Model Input	Under Study?	Data Source	Value Distribution	Value
Arrival Rate	No	Clinic Scheduling	Negative Binomial	1.6/day
Continuing to Partnership	Yes	Clinic Scheduling	Uniform	65%
Number of Appointments	Yes	Clinic Scheduling	Negative Binomial	6.5/client
No-Show Rate	Yes	Clinic Scheduling	Uniform	9%
Number of FTE	Yes	Job-Planning	Average over one year	11.5
Skillset Demand	Yes	Professional Opinion	Discrete	Uniform
Choice Blocks	No	Job-Planning	Average over one year	5.5
Partnership Blocks	No	Job-Planning	Average over one year	40.5

4.4 Model Outputs

The model outputs were determined by discussion with process experts and their experience with metrics used through the clinic's Lean activities. Moreover, some outputs were used as they are in line with provincially reported metrics and allow comparison of changes when compared to historic data. The three types of times reported were: 1) time from referral (arrival) to Choice; 2) time from Choice to first Partnership and; 3) time between subsequent Partnership appointments. These first two wait times have been used in previous literature, in addition, the NS Department of Health and Wellness uses the referral to Choice as a routine metric (11). These times are used for decision making when planning jobs in the subsequent quarter and can indicate the level of client flow. The output times are a strong indicator of access and client flow, used both provincially and within the IWK CMHA clinics, making them natural metrics to use as model output. Lastly, the number of clients who had an appointment within the wait-time benchmark (28 days for Choice, 14 days for first Partnership after Choice) was recorded as a percentage of all clients seen.

4.5 Model Flow and Logic

The following sections outline the process of the algorithmic model, as carried out by the computer and syntax. The simulation model was implemented using Microsoft Excel and coded using VBA [30]. This software was used as all clinics had access, were comfortable with the interface, and would incur no additional costs. 4.4 outlines the computational steps of the simulation at the level of each algorithm or process informed by the conceptual model (as outlined in figure 4.1).

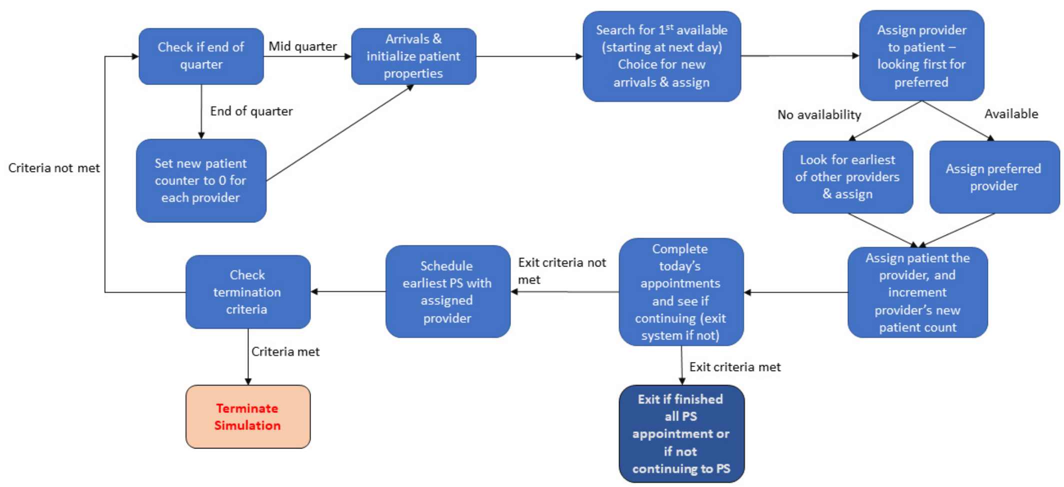

Figure 4.4: Schematic Overview of the Choice-to-Core-Partnership Pathway Simulation Model

4.5.1 Model Initialization

At the start of each replication, the simulation reads in the input parameters and indices. The length of the replication and number of providers are read in to generate a two-dimensional VBA collection for each day of a year, for each provider [1]. These collections act as the

[1] A VBA collection is an object that stores items as an ordered set (https://docs.microsoft.com/en-us/office/vba/api/overview/)

provider's calendar into which clients are scheduled, added to, and removed from. After the collections are created, the model then creates a capacity as a property of the schedule collection, for both Choice and Partnership, based on the defined capacity inputs.

After the schedule for each provider has been created, a custom object "provider" is set for each user-defined provider and added to a new collection to allow for indexing and referencing of all listed clinicians. The skillset is a property of the provider object and is read in from an input spreadsheet, subsequently setting the clinician name property to sequential integers. Lastly, providers are assigned a property to track maximum number of new clients in a quarter, clients added in the next two quarters, and running average wait time. These properties, except for wait time, are calculated within the spreadsheet and then read into the provider class object to be stored. Wait times are calculated on an ongoing basis within the model. At this point the collections and providers have been initialized with starting values and are prepared to be used within the simulation. All values are reset to baseline if specified, or 0, at the start of a new replication.

4.5.2 Arrival Process and Client Properties

At the start of each day, the model checks to see if it is the end of a quarter, as this signifies a provider's ability to accept new clients, by resetting their current client count to 0, allowing the model to add new clients to a provider's schedule. At the end of each quarter, a Partnership appointment will be added if provider specific wait times exceed a threshold. This is done with the assumption that a new quarter happens every 91 days. Upon completing the quarterly check, the model checks whether it is a weekend (*i MOD 7* equaling 5 or 6), as it will set daily arrivals to 0 if this condition is met. Otherwise the model generates a random negative binomial variate from a user defined mean (size parameter is hard-coded to match the results of input data analysis), as the number of clients arriving for services that day. For each daily arrival, a name is given to the client, set as the "arrival number – day" (i.e. 1-1 for first on day one, and 1-2 for the first arrival on day two). Next, the number of Partnership appointments is drawn from a negative binomial distribution with a user defined mean (again with a predetermined size parameter); clients who will not continue to Partnership appointments have this parameter set to 999.

Two more client properties are assigned to the daily client arrivals, the inter-arrival time (IAT) and a clients' preferred skillset. The skillset is determined using a cumulative distribution function and a random number generator within Excel. The user-defined skillset table is based on professional opinion of the distribution of skillsets within the clinic and expected demand for specific skillsets of providers (see table 4.5). A uniform random value $X \sim U(0,1)$ is drawn and determines the client's preferred skillset from empirical distributions. For example, if a variate drawn is 0.3 the program will find which provided is bounded by this value and assign the client preference. Lastly, IAT increases throughout the course of treatment and is initialized at 7 days for a client's first Partnership appointment, which is increased using the ratio of completed to maximum partnership sessions, calculated as the current appointment divided by the maximum required appointments.

Table 4.5: Skillset demand input parameters model

Skillset	**% Demand**	**Probability**
1	0.333	0.33
2	0.333	0.66
3	0.334	1.00

4.5.3 Choice Appointment Search Function

Now that the daily arrivals have been initialized and assigned properties, the model runs a search algorithm to find the initial Choice appointment for each daily arrival. Although clients can be screened out of Partnership appointments, all clients will undergo the Choice appointment for goal assessment and determination of service or support requirements. Choice appointments do not require a preferred provider skillset and therefore the search looks for the earliest available Choice appointment across all providers, with Choice appointments available. Starting with the day after the current day, the search looks across all providers for available Choice capacity, and with no data collected on no-show rates at Choice, it is assumed all appointments are attended. When this is found, the client is added to the providers' schedule collection, the provider's Choice capacity is reduced by one, and the search ends. If an appointment cannot be found in the timeline of the simulation an error is raised and the simulation is terminated.

4.5.4 Partnership Provider/Appointment Search Function

The model has now handled all steps required for daily arrivals and begins the process of managing the current day's scheduled appointments. For each provider, a loop begins to check whether there are any appointments for the day, and if so, the algorithm will implement steps to schedule subsequent appointments, increment counters, and collect statistics. For each client on a provider's schedule, the algorithm assesses whether the client requires more sessions (current count < total count), has met all sessions (current count = total count), or is not continuing to Partnership (current count = 999). Those who do not require further sessions are taken off the current day's provider's schedule, with provider capacity being incremented for either Choice (current count = 0) or Partnership (current count ≠ 0) and exit the system.

If the scheduled appointment completed was a Choice appointment, the search algorithm for a preferred skillset is undertaken for assigning the first Partnership appointment. First, for each day (starting at the day after current) the provider search function looks for open capacity in the client's preferred skillset providers, that meet the following conditions: 1) the provider has availability; 2) the time to appointment would be less than 80 days and; 3) the provider has room to accept new clients. The 80-day threshold represents the compromise of finding a preferred skillset with the time spent waiting for this skillset. If the preferred skillset can be assigned from a provider meeting the conditions, the model exits the search and continues to the next steps. If a preferred skillset cannot be assigned, the next available provider is then assigned to the client. Based on the assignment conditions, the provider's current patient amount is incremented for current, next, or after subsequent count.

After the provider is assigned and remaining inside the loop for each client on a provider's schedule, a Partnership search function is implemented to look for the next available appointment in a given provider's schedule. The IAT is updated following each assignment of a subsequent Partnership appointment. IATs are assigned to one of three categories based on the attended number of appointments, divided by the total number of appointments to be attended. As clients progress in the model the IATs increase, representing the increase in time between Partnership appointments over the duration of treatment. Taking into account the required IAT determined above (search start = today + IAT), an appointment search is conducted. Once an available slot is found for the assigned provider the client is added to the provider's schedule, capacity is decremented by one, and the wait time is collected in either time to first (current= 0) or time between (current > 0) Partnership appointments both globally and for each provider.

Lastly, a random number is generated $X \sim U(0, 1)$ to account for no-shows, using the criterion specified at run time. A no-show is kept on the providers' schedule but the number of appointments for the client is not incremented to represent lost capacity with no forward movement in treatment course. This process is repeated for every client on each provider's schedule for the current day, with statistics updated at the end of the day. The model then advances to the next day and begins the process again, until the termination criterion (simulation length) is met.

4.6 Model Assumptions

As is standard in any abstraction of a real-world system, the model required a number of assumptions and simplifications. These assumptions may lack data sources to confirm, or are used to remove extraneous variability in the system. Table 4.6 outlines all assumptions and simplifications.

Table 4.6: Simplifications and assumptions used in the model

Concept	Values	Role in Model	Source of assumption
IAT between treatment	7, 12, and 14 days	Taper of appointments as treatment progresses.	Professional opinion
Preferred skillset search	80 days	Search for 80 days before looking for next available provider	Professional opinion, and max waits
Days in quarter	91	Tracks counters and moves time	Simplify time tracking
Core Blocks	40%	Percent of FTE blocks allocated to Core activities	CAPA Guidelines
Skillsets	3	Arbitrary, but represents heterogeneity of skills	Professional opinion
Choice Search	+1	Cannot find appointment same day as arrival. Lowest wait time is 1 day	Booking clerk experience

4.7 Run Parameters

A M/M/s system is a standard queuing model that assumes a single queue, with a Poisson arrival process, exponential service times, and s servers [29]. Given the simplicity of the simulation model and its similarity to a M/M/s queuing system, a replication-deletion method was used as the warm-up had little impact on computational resources and avoids a time-lag bias associated with batch-means [29]. Welch's method was used to determine the warm-up period by looking for the steady state within the baseline model, with a moving average of $w = 7$. Figure 4.5 demonstrates the graphical method, using time to Choice appointment. It was determined that a year-long warm-up was sufficient to remove initial condition bias and collect statistics from a steady state system at baseline.

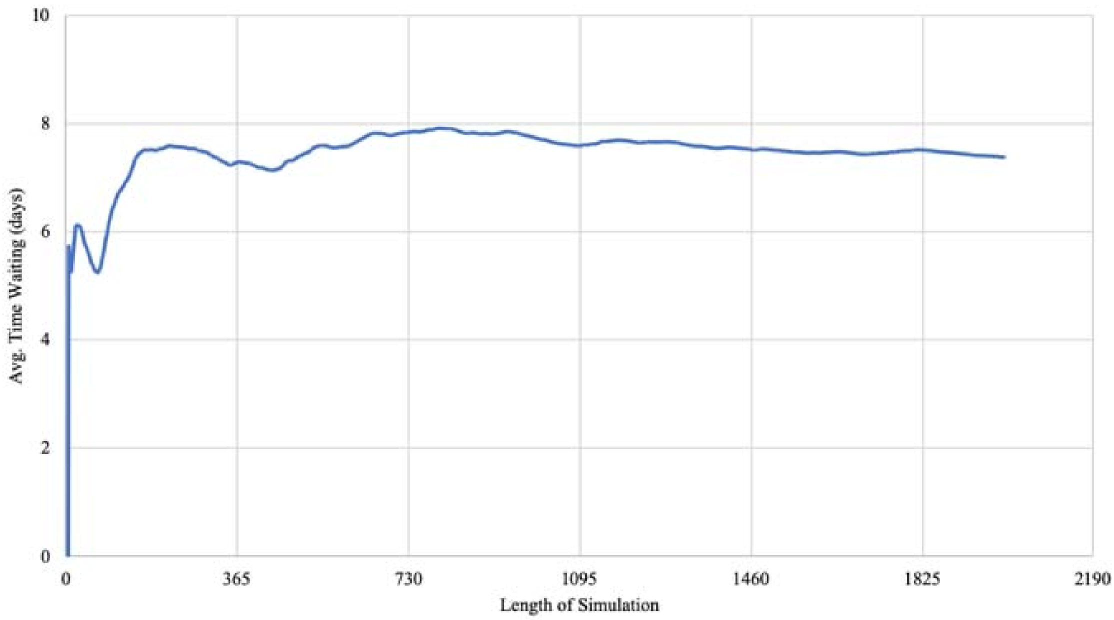

Figure 4.5: Wait until Choice over simulation time

The length of each replication was determined by ensuring rare events could occur multiple times throughout the simulation. A rare event was defined as a number of appointments greater than 20, which happens fewer than 10 times in a year, based on the clinical data. Therefore, the simulation replicate length was set to 5 years, to allow for this rare event to occur multiple times. The probability of not seeing an appointment greater than 20 in 5 years is 3.52×10^{10}% (96 clients per year, with 65% having Partnership appointments, and the probability that a random variate from the negative binomial distribution is not greater than 20). Lastly, the number of replications required enough precision to allow for significant differences, without providing a false sense of precision with too many replicates. Running 5 replications provided a margin of error of ~1 day in estimates for wait times and ~10 days for total time in system. Given this level of precision, 5 replications were used. The equation to determine the number of replications is shown in equation 4.1, with the table 4.7 as the results from the goal-seeking procedure.

$$n \geq \left(\frac{t_{n\ 1,\frac{\alpha}{2}} S}{E} \right)^2 \tag{4.1}$$

Table 4.7: Results from calculations to determine the number of replications in the simulation

Parameter	**Result**
α	0.05
E	2
S	1.46
n	5
t	2.78
Half Width	1.81

4.8 Model Validation and Verification

Model validation predominantly came from iterative and structured walkthroughs with process experts to ensure all processes were being performed as expected and understood within the system and as specified by CAPA's guidelines [12]. Process experts included for validation were clinic managers, clinicians, industrial engineers, and data custodians. Revisions to the model were made following an iterative process to ensure all inputs, model processes, and outputs were correctly representing the real-world system as required. In addition to ensuring the model was correct in its system representation, revisions were made to include language and visual output that would be relatable to clinicians and model users, to avoid confusion about model components.

The first approach to model verification was ensuring model components followed equations derived from queuing theory for an M/M/s system. Given the rate of arrivals ($lambda$), the rate of service (μ), and the number of providers (s), steady-state values can be calculated. The time in system was used to compare and is derived with a number of standard equations (see [31] and below). Initially, eq. 4.2 is used to calculate the traffic intensity, which indicates if a system will reach a stable state, when $\rho < 1$. Using ρ from eq. 4.2 the probability of there being zero clients in the queue, (π_0), can be calculated using eq. 4.3. Using π_0, the steady-state probability that all servers (s), are busy with clients (j) (L_q), in eq. 4.4. L_q (eq. 4.5) can now give rise to average number of clients in the system, (L) eq. 4.6, which is finally used to define our metric of interest, average time in system, (W) eq. 4.7.

$$\rho = \frac{\lambda}{s\mu} \tag{4.2}$$

$$\pi_0 = \frac{1}{\sum_{i=0}^{s-1} \frac{sp^i}{i!} + \frac{sp^s}{s!(1-p)}} \tag{4.3}$$

$$P(j \geq s) = \frac{(s\rho)^s \pi_0}{s!(1-\rho} \tag{4.4}$$

$$L_q = \frac{P(j \geq s)\rho}{1-\rho} \tag{4.5}$$

$$L = L_q + \frac{\lambda}{\mu} \tag{4.6}$$

$$W = \frac{L}{\lambda} \tag{4.7}$$

The steady state equations were compared to simulation results using an arrival rate of 1.6 clients per day, and the number of providers was set to six with one appointment per week, with another provider with two appointments per week, as to allow for a steady-state system in which ρ is less than 1.0. This translates into a service rate of 0.228 clients per day for each of the seven providers. The selection of providers and arrivals is arbitrary, but must allow for steady state to compare model output with the steady state equations. The output focussed only on the time to Choice, as this functions as the closest to a first-in-first-out discipline, and additional complexity violated the M/M/s assumptions past the Choice appointment. Figure 4.6 shows the results of the model for Time to Choice, with a 95% confidence interval, compared to the results of the queuing equations for a M/M/s system. It is clear that the syntax is behaving as expected for this component of the model, given no significant difference from the steady state output of the equations and simulation results.

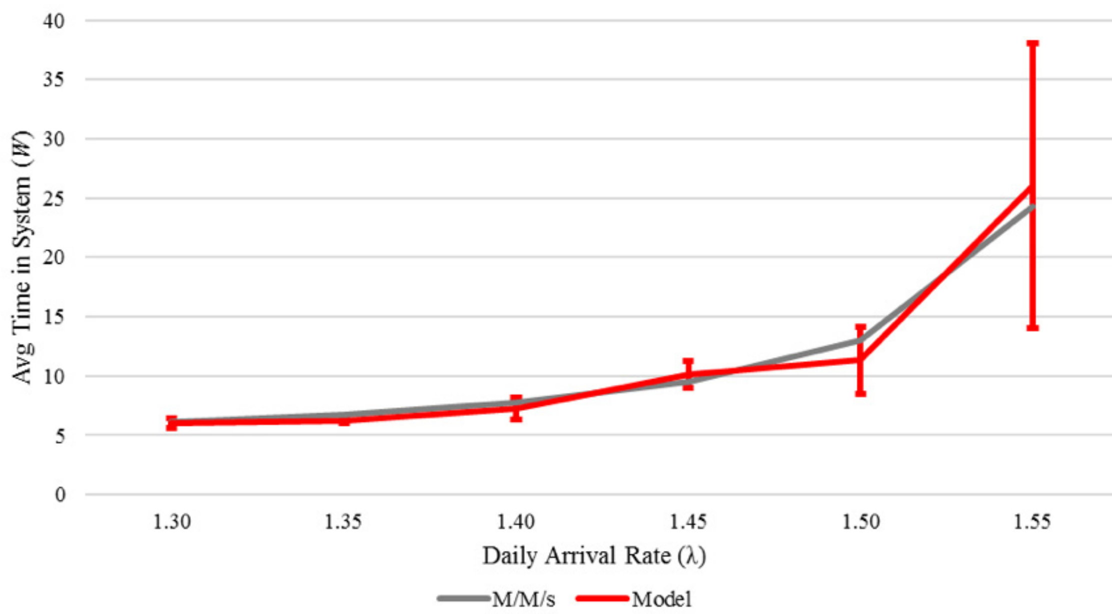

Figure 4.6: Results of an M/M/s queuing system against simulation output

A number of other validation and verification techniques discussed in Sargent and Law were performed to ensure a verified and valid model [32, 29]. The above comparison also represents a degeneracy test, such that the response of the outcome, wait time, reacts in a predictable manner to a shift of input parameters rate of arrivals. Moreover, testing of extreme values (i.e. fewer than 0.5 daily arrivals, and an average of two appointments), results in expected values, where wait times are roughly equal to the predetermined IAT within the model, therefore almost no time spent waiting. All input distributions were tested to ensure they did not significantly differ from the historical data, using a Chi-squared test for validity. Lastly, face validity was ensured through the iterative process of engaging experts for structured walk-throughs of the model and validating results to ensure outputs react appropriately to changes from input parameters.

Following the verification revisions to the model, face validity was ensured through the iterative process of engaging experts for structured walk-throughs of the finalized model to ensure outputs react as expected to changes from input parameters. The walk-through first went over every model step, and how it translated back into the real-world system it is aimed to represent. This confirmed we had captured the components intended to model, and not misrepresented any steps included in the model. After this walk-through, a number of test runs were shared to demonstrate the effects of model output, based on changes made to model input. This confirmed the model behaved in an expected manner, and process experts agreed with the model's baseline scenario settings.

The goal of the simulation model and its validation was not to match the CAPA system *in situ* at the study clinic, but rather to generate a model that matches how the Choice-to-Core-Partnership Path is intended to operate, with the ability to modify input parameters to match clinics under study. Therefore, we did not perform output analysis of the baseline model against collected and analyzed data as the simulation does not aim to replicate the study clinic as it behaves during the study period.

Chapter 5: Results

5.1 Knowledge-to-Action Cycle

Engaging process experts at the beginning of the research fostered an environment of communication and learning. These discussions demonstrated the clear need to have a tool that could communicate the impact of system changes to clinicians, managers, clinical leaders, and the Director. Adapting the research to the local context resulted in the identification of guiding principles of CAPA that may be a challenge to implement in the CMHA clinics, such as identifying specific clinical skillsets rather than profession (e.g. social work or psychology), as clinical positions are identified by profession at present. Accordingly, the model was developed to consider skillsets of clinicians, rather that their professional designations, as designations do not preclude specific skillsets and vice versa.

Discussions with process experts, such as the CAPA Advanced Practice Lead, booking and registration clerks, data custodians, and clinicians served to identify knowledge gaps and tailor the model to provide useful information to support decisions. A key component of these discussions was the ability to use collected data in a meaningful and accessible way. A quote from one process expert summarized some frustrations by saying: ". . . we invest tons of time putting the data in so why can't we get it out easily?". This demonstrated the desire to see collected data and use it to support decision making in the clinic, supporting the need for a tool as a facilitator for new knowledge diffusion.

Wait times provided a primary outcome measures as government and policy stakeholders widely report this metric, in addition to it being a quantifiable and communicable value that speaks to many people. Part of implementing future knowledge interventions was to facilitate interactive meetings where clinicians and process experts can be walked-through the model and results, understand all assumptions and inputs, and provide feedback about the validity of the simulation approach.

While monitoring knowledge use and evaluating outcomes are outside the scope of this thesis, this research sits within a larger programme of research that aims to look at CAPA implementation, needs-based job planning, client and system outcome measurement, and making data driven decisions [33]. The development of a generalizable, scalable model was undertaken to support the evolution and monitoring of wait times, and to allow for extension to incorporate measures of the quality of care.

The sustainability of knowledge use was supported through a number of choices. Firstly, it was a goal to use data that are accessible and routinely collected to allow for reproducibility as time progress, in addition to requiring limited resources to extract these data. Additionally, VBA and Microsoft Excel were selected due to familiarity with Excel within the clinic and integration with existing systems, with the resulting model output in Figure 5.1 [30].

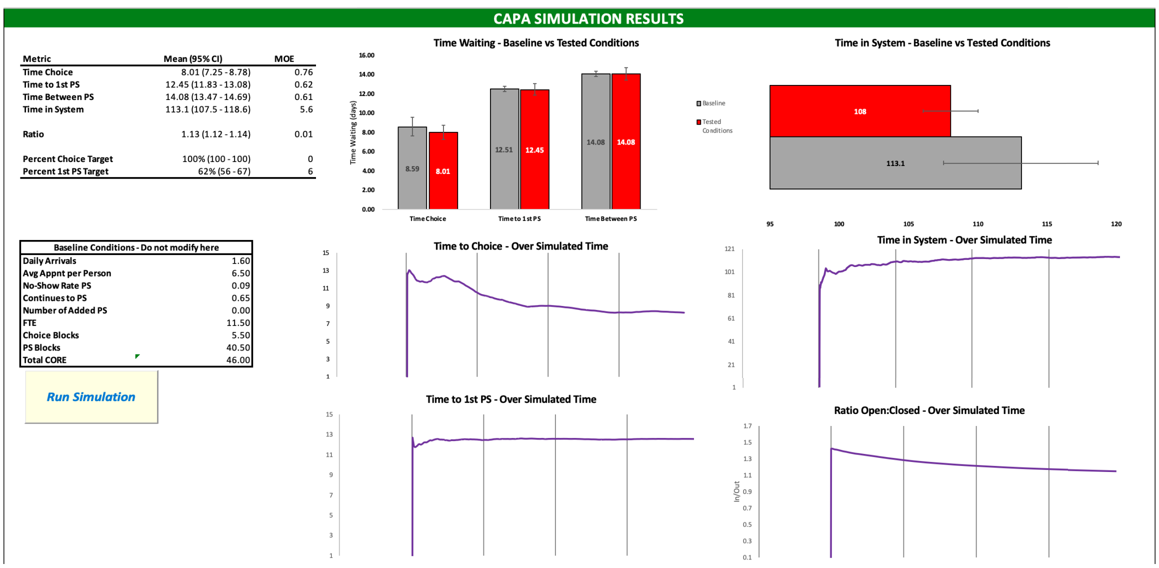

Figure 5.1: Simulation results printed to an Excel workbook for viewing.

5.2 Baseline Scenario

The baseline scenario acted as the control, or comparator, to measure the relative impact of each system factor individually. Baseline results do not represent real-world outcomes, but rather a steady-state scenario that can act as a stable point of reference as other factors are varied. The current system at the time of study was not in steady-state and the developed model did not aim to capture the entire system, which led to using a baseline scenario that was steady-state and not the current system. The resulting wait times from the baseline model, given as the mean (95% confidence interval), were 9.1 (7.8-10.4) days spent waiting for a Choice appointment, 12.6 (12.4-12.9) days spent waiting for the first Partnership appointment, and 14.2 (13.9-14.4) days spent waiting between Partnership appointments. Total mean wait times (combined waits to Choice, to first Partnership, and between Partnership appointment) resulted in 108.6 (105.4-111.8) days spent within the system, or a little over 3.5 months to complete treatment. On average, 99% (97%-100%) of clients met the Choice target of fewer than 28 days waiting, in addition to 58% (55%-61%) meeting the first Partnership target of fewer than 14 days waiting.

5.3 System Factor Variations

As mentioned above, five system factors were varied, with multiple settings per parameter. The results from these experiments were split into two groups where 1) is the time to and between appointments; and 2) the overall time in system and wait time benchmark attainment for Choice and first Partnership. Each table specifies the setting of the parameter, with the baseline setting starred to compare the results. The baseline result remains the same in each table and acts as the comparative control as the parameters are varied individually.

5.3.1 Percent of Clients Continuing to Partnership

As the demand for Partnership appointments increases, wait times to and between Partnership appointments increase exponentially and the system becomes increasingly unstable. Figure 5.2 graphically demonstrates the nonlinear growth as demand increases, excluding the time to Choice, which remains stable. Instability is demonstrated through the increasing confidence intervals as variance in the system grows. Increasing the percentage of clients who continue to Partnership appointments adds demand only for services after the Choice appointment, and this is reflected in the non-significant changes between settings for time to Choice appointments presented in Table 5.1. Given that the system was stable at baseline, there are modest reductions in wait times as demand is reduced below baseline. A common result throughout the scenarios is the increase in time between Partnership appointments is slightly greater than the time to the 1st Partnership appointment. This is likely due to the imposed increases in IAT between appointments, and this required time between appointment inflates the average time between subsequent Partnership appointments.

Table 5.1: Time to, and between, Partnership, and Choice for each setting of the percent who continue to Partnership. Mean (95% Confidence Interval).

Continue to Partnership (%)	**Days to Choice**	**Days to 1st Partnership**	**Days Between Partnership Sessions**
50%	8.41 (6.42-10.4)	10.52 (10.26-10.77)	12.54 (12.36-12.72)
60%	7.88 (6.74-9.02)	12.38 (10.94-13.81)	14.22 (12.68-15.76)
65%*	9.12 (7.84-10.4)	12.63 (12.37-12.9)	14.18 (13.88-14.49)
70%	8.47 (7.7-9.23)	13.77 (12.82-14.72)	15.32 (14.44-16.21)
75%	8.87 (7.67-10.08)	22.69 (20.43-24.95)	24.14 (21.96-26.33)
80%	9.3 (7.56-11.04)	28.13 (26.10-30.17)	29.41 (27.46-31.36)
85%	9.14 (6.56-11.73)	31.92 (28.69-35.14)	33.69 (30.00-37.37)

* Baseline Scenario Setting

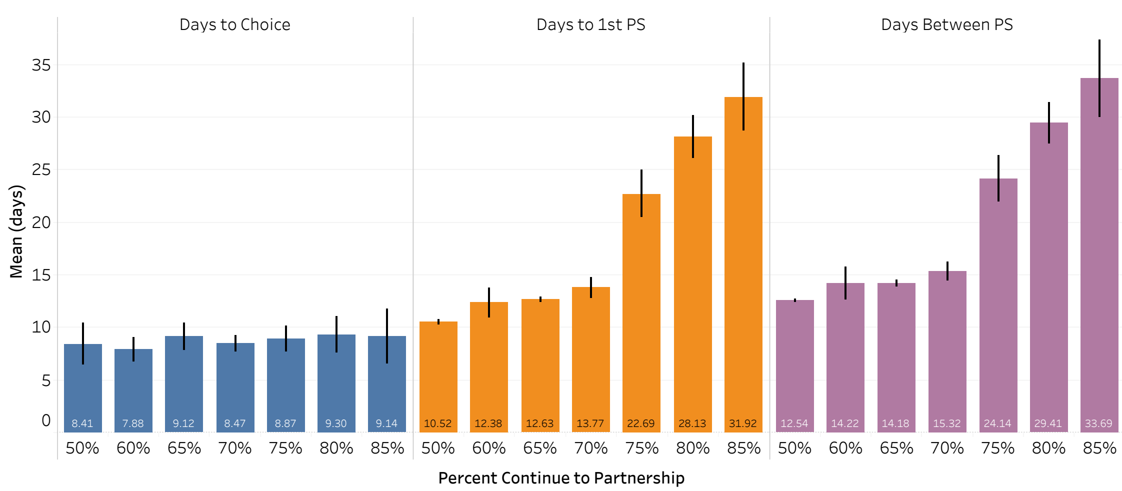

Figure 5.2: Average wait time change, and 95% error bars, as the demand for Partnership services in modified

The benchmark attainment for Choice remains stable even as demand for Partnership is increased; however, the rate of attainment drops for 1st Partnership (see Table 5.2. As expected, the overall time in system increases as the waits to 1st and subsequent Partnership appointments increase. There is a higher increase of Partnership benchmark attainment as the demand is decreased demonstrating that, although overall wait time reduction is modest, wait time would have less variation.

Table 5.2: Time in system and target attainment for each setting of the percent who continue to Partnership. Mean (95% Confidence Interval).

Continue to Partnership (%)	**Days in System**	**% Choice Benchmark Met**	**% Partnership Benchmark Met**
50%	94.6 (91.6-97.7)	99 (96-101)	82 (79-85)
60%	106.8 (93.9-119.7)	100 (99-100)	66 (58-73)
65%*	108.6 (105.4-111.8)	99 (97-101)	58 (55-61)
70%	114.0 (107.5-120.5)	100 (99-100)	50 (44-56)
75%	162.4 (151.1-173.6)	99 (97-101)	24 (21-28)
80%	189.6 (178-201.2)	98 (95-102)	11 (8-15)
85%	214.3 (191.5-237.2)	98 (95-101)	9 (4-14)

* Baseline Scenario Setting

5.3.2 FTEs in Clinic

The loss of FTEs is the only system factor that causes an increase in the wait for Choice, shown in Tables 5.3 and 5.4. The loss of an FTE has a widespread impact that significantly reduces the available number of Partnership and Choice blocks within the system, yet the magnitude of the effect is smaller compared to other system factors. It becomes clear that most of the system factors tested impact the Partnership processes of the Choice to Core-Partnership flow, with the exception of FTEs in the clinic. The last parameter of total FTEs tested three settings beyond the baseline value of 11.5; losing one, losing two, and gaining one FTE at the clinic. Figure 5.3 shows the large impact FTE changes have on the Choice wait times in addition to the system instability based on the level of error.

Table 5.3: Wait time results for each setting for total number of FTEs. Mean (95% Confidence Interval).

FTEs in Clinic	Days to Choice	Days to 1st Partnership	Days Between Partnership Sessions
12.5	6.05 (5.76-6.34)	11.86 (11.65-12.07)	13.39 (13.05-13.74)
11.5*	9.12 (7.84-10.40)	12.63 (12.37-12.90)	14.18 (13.88-14.49)
10.5	34.91 (14.96-54.87)	16.54 (14.13-18.95)	18.05 (15.76-20.33)
9.5	51.11 (41.26-60.96)	21.07 (17.46-24.68)	22.49 (18.94-26.04)

* Baseline Scenario Setting

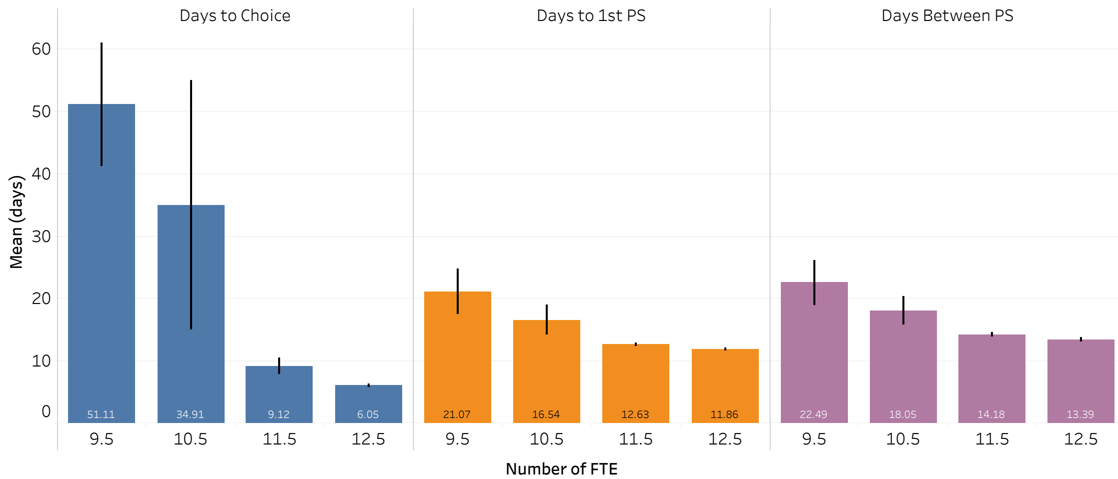

Figure 5.3: Average wait time change, and 95% error bars, as the number of FTE changes from baseline. Note the y-axis has been increased from previous figures to capture days to Choice.

Time in system increases as FTEs are reduced, with large changes in percent of benchmark attainment for both Choice and Partnership, as seen in Table 5.4. As in other instances, when increases to resources creates a stable system, there are modest gains in attainment of wait time benchmarks for the Choice and Partnership appointments.

Table 5.4: Time in system and goal attainment results for each setting for total number of FTEs. Mean (95% Confidence Interval).

FTEs in Clinic	Days in System	% Choice Benchmark Met	% Partnership Benchmark Met
12.5	99.4 (96.6-102.3)	100 (100-100)	68 (66-70)
11.5*	108.6 (105.4-111.8)	99 (97-101)	58 (55-61)
10.5	152.7 (134.6-170.8)	54 (29-80)	45 (42-47)
9.5	193.8 (174.3-213.4)	17 (1-33)	26 (15-37)

* Baseline Scenario Setting

5.3.3 Skillset Demand Discrepancy

The results follow a linear increase in waits as the discrepancy between the balance of skillsets increases for each test setting, see Figure 5.4 and Table 5.5, but still had a smaller relative impact on waits compared to the previously presented system factors. Choice appointments are not assigned to individual clinicians, but a group of clinicians with the Choice skillsets, therefore we see no significant differences for the Choice waiting times. The wider confidence intervals demonstrate how quickly the system reaches instability as the discrepancy is increased, shown in Figure 5.4. Similar to the baseline values for the rates of no-shows, there were no levels below baseline tested for skillset demand, as the baseline was set to even demands.

Table 5.5: Wait time results for each setting for balance of skillset demand with three skillsets, Mean (95% Confidence Interval).

FTE Skillset Balance	Days to Choice	Days to 1st Partnership	Days Between Partnership Sessions
33/33/33*	9.12 (7.84-10.4)	12.63 (12.37-12.9)	14.18 (13.88-14.49)
40/35/25	8.35 (7.46-9.25)	16.34 (12.72-19.96)	18.06 (14.45-21.68)
40/40/20	8.34 (7.53-9.15)	18.83 (15.2-22.47)	20.42 (16.98-23.85)
50/25/25	9.04 (7.69-10.38)	25.02 (23.79-26.26)	26.21 (25.37-27.04)

* Baseline Scenario Setting

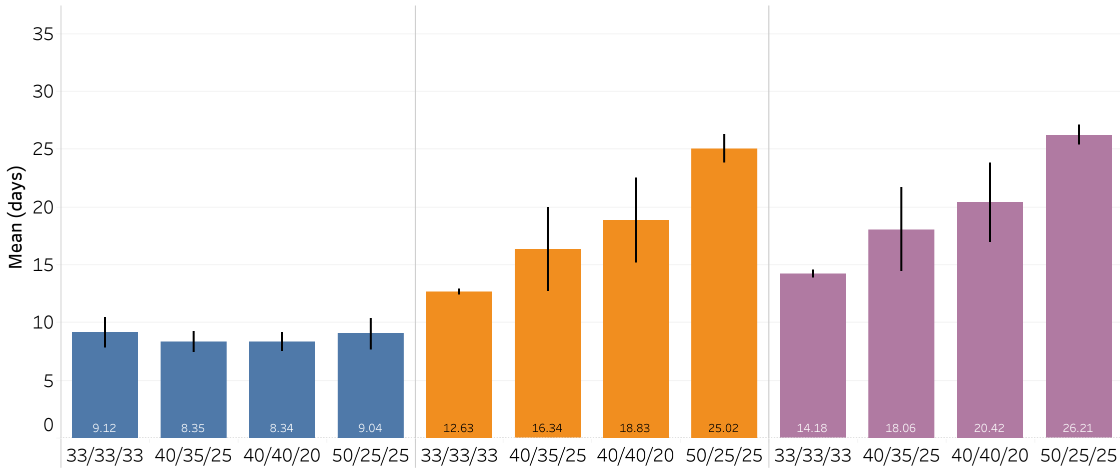

Figure 5.4: Average wait time change, and 95% error bars, as the demand discrepancy is increased

Table 5.6 shows the total time in system and percent benchmark attainment as demand discrepancy is increased. The reduction of Partnership benchmark attainment is somewhat more modest than the previous factors, reaching 10% higher than the increase for no-show rates at the highest level of increase.

Table 5.6: System time and goal attainment results for each setting for skillset demand discrepancy. Mean (95% Confidence Interval).

FTE Skillset Balance	**Days in System**	**% Choice Benchmark Met**	**% Partnership Benchmark Met**
33/33/33*	108.6 (105.4-111.8)	99 (97-101)	58 (55-61)
40/35/25	129.4 (106-152.8)	100 (100-100)	49 (40-58)
40/40/20	142.7 (122.5-162.9)	100 (100-100)	40 (32-47)
50/25/25	179.9 (173.4-186.4)	99 (97-101)	44 (42-46)

* Baseline Scenario Setting

5.3.4 Number of Appointments

As the mean number of Partnership appointments increases, the system becomes unstable and wait times exhibit a non-linear increase. Moreover, as the mean number of Partnership appointments are varied, time to Choice remains stable, with the time to 1st Partnership and between appointments increasing, shown in Table 5.7 and Figure 5.5.

Table 5.7: Wait time results for each setting for the number of Partnership appointments. Mean (95% Confidence Interval).

Mean Partnership Sessions	**Days to Choice**	**Days to 1st Partnership**	**Days Between Partnership Sessions**
5.0	8.54 (7.63-9.46)	10.83 (10.69-10.96)	12.7 (12.58-12.81)
6.0	7.71 (7.00-8.42)	11.48 (11.28-11.69)	13.25 (13-13.5)
6.5*	9.12 (7.84-10.4)	12.63 (12.37-12.90)	14.18 (13.88-14.49)
7.0	8.76 (6.89-10.63)	14.58 (13.33-15.83)	16.02 (14.87-17.17)
7.5	8.47 (7.39-9.54)	18.24 (16.49-19.98)	19.75 (18.03-21.47)
8.0	9.02 (7.04-10.99)	24.66 (20.32-29.00)	26.11 (21.7-30.53)
8.5	9.14 (6.82-11.46)	29.72 (25.26-34.17)	31.3 (26.58-36.02)

* Baseline Scenario Setting

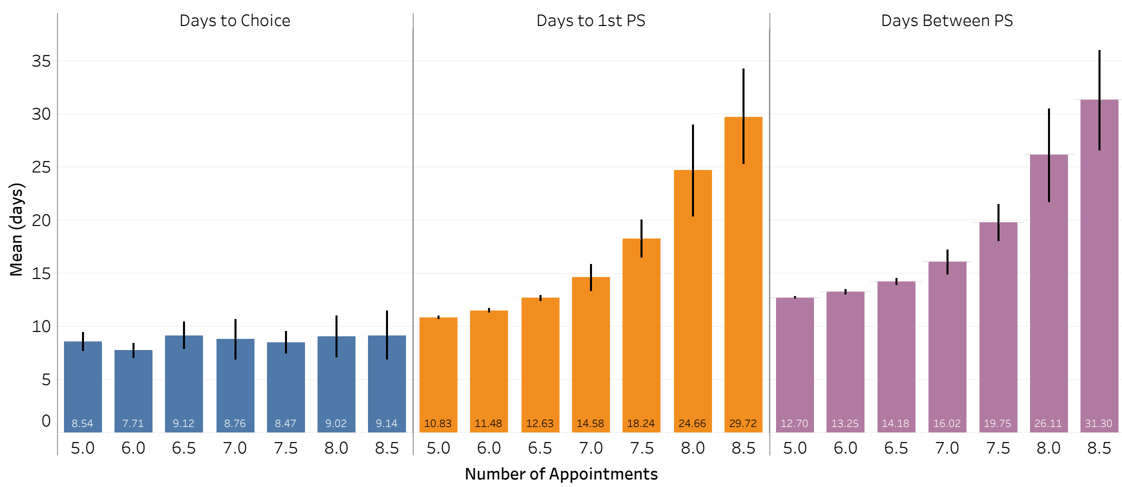

Figure 5.5: Average wait time change, and 95% error bars, as the number of Partnership appointments in modified

Lastly, the patterns are again mirrored for the time in system and percentage attainment of benchmarks when comparing demand for Partnership and number of Partnership appointments, shown in Table 5.8. The time in system is slightly higher, as the number of appointments will increase a client's overall service time.

Table 5.8: System time and goal results for each setting for the number of Partnership appointments. Mean (95% Confidence Interval).

Mean Partnership Sessions	Days in System	% Choice Benchmark Met	% Partnership Benchmark Met
5.0	75.1 (73.9-76.3)	100 (99-100)	79 (78-80)
6.0	92.4 (91.2-93.6)	99 (97-101)	72 (69-74)
6.5*	108.6 (105.4-111.8)	99 (97-101)	58 (55-61)
7.0	125.9 (118.5-133.3)	98 (94-102)	48 (43-53)
7.5	158.7 (146.8-170.5)	99 (97-101)	31 (27-35)
8.0	208.7 (177.8-239.6)	98 (95-101)	19 (11-27)
8.5	253 (216.2-289.7)	98 (95-102)	12 (5-18)

* Baseline Scenario Setting

5.3.5 No-Show Rate for Partnership

The rates of no-show for Partnership appointments had less impact on wait times, (see Table 5.9), compared to the previous two parameters. It is clear that a large increase in no-show rate is required to achieve a significant difference from the baseline setting. Figure 5.6 demonstrates that the relationship between wait time and no-show rate is approximately linear as the no-show rate is increased. This was also demonstrated in the time in system and goal attainment results (Table 5.10). The baseline factor setting of 9% is uncharacteristically low for the rates of no-shows in a community mental health clinic, but this was expected given the intense efforts to achieve attendance at the study clinic. For these reasons, the rate of no-show was only increased, as opposed to decreased as it represents a largely improbable rate when below 9%.

Table 5.9: Wait time results for each setting for no-show rates of Partnership appointments. Mean (95% Confidence Interval).

% Partnership No-Show	Days to Choice	Days to 1st Partnership	Days Between Partnership Sessions
9%*	9.12 (7.84-10.4)	12.63 (12.37-12.9)	14.18 (13.88-14.49)
12%	7.84 (7.1-8.57)	14.26 (11.33-17.19)	15.97 (12.94-19.01)
15%	7.97 (6.88-9.06)	15.35 (13.2-17.5)	17.03 (14.91-19.15)
20%	7.98 (7.2-8.77)	18.27 (16.2-20.35)	19.89 (17.82-21.95)
25%	8.37 (8.06-8.69)	20.3 (19.08-21.51)	21.97 (20.63-23.31)

* Baseline Scenario Setting

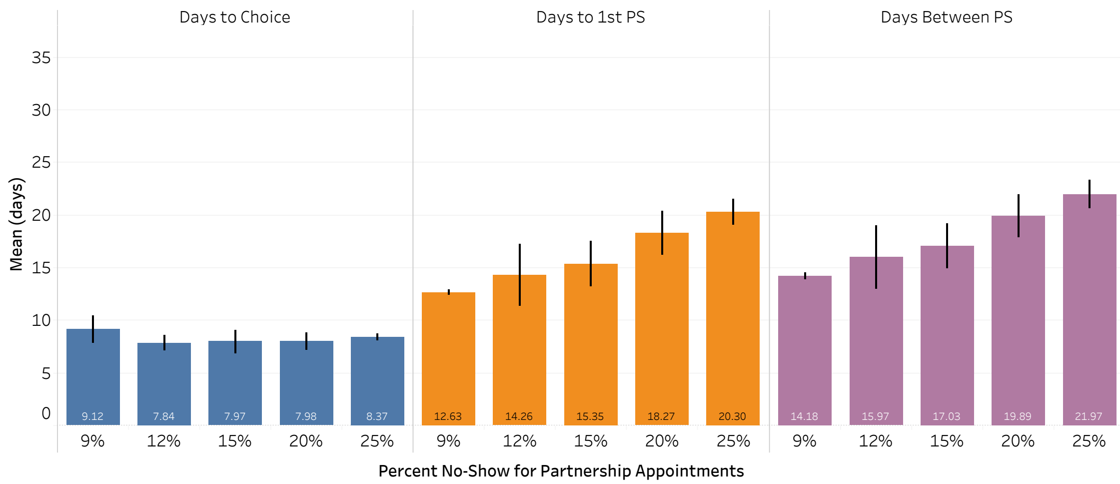

Figure 5.6: Average wait time change, and 95% error bars, as the rate of no-shows for Partnership appointments is increased

Table 5.10: System time and goal attainment results for each setting for no-show rates of Partnership appointments. Mean (95% Confidence Interval).

% Partnership No-Show	Days in System	% Choice Benchmark Met	% Partnership Benchmark Met
9%*	108.6 (105.4-111.8)	99 (97-101)	58 (55-61)
12%	120.7 (101.1-140.3)	100 (100-100)	57 (50-65)
15%	132.8 (119-146.6)	100 (100-100)	49 (41-57)
20%	156.9 (140.7-173)	100 (100-100)	40 (34-47)
25%	183.3 (171.5-195.1)	100 (100-100)	34 (27-42)

* Baseline Scenario Setting

5.4 Additional FTE to Maintain Steady State

Increases to the percentage of clients continuing to Partnership and mean number of Partnership appointments required the most additional FTE to prevent increases in wait times (Table 5.11. This supports the hypothesis that both of these system factors had the largest relative impact on wait times, as they require the most additional human resources to prevent an increase in wait times. The settings for each parameter were selected as the first level that had a significant difference, with the exception of number of Partnership appointments. A mean of 7.5 appointments was selected as this was determined to be within the average number appointments mentioned in CAPA guidelines, and was requested by process experts.

Table 5.11: Additional FTE required to achieve steady state for specific changes in system factors

System Factor	Setting Change	New FTE (Total)	Days to 1st Partnership
Baseline Scenario	Reference	Ref. (11.5)	12.63 (12.37-12.90)
Continue to PS	65% to 75%	+1.5 (13.0)	12.57 (11.57-13.57)
Number of Appts	6.5 to 7.5 per client	+1.5 (13.0)	13.25 (12.09-14.41)
Skillset Demand	Uniform to 40/35/25	+0.5 (12.0)	13.21 (12.15-14.27)
No-Show Rate	9% to 15%	+0.5 (12.0)	12.45 (11.83-13.08)

The results align with the relative impacts seen in the previous section. Therefore, parameters that result in larger increases in wait times, such as percent continuing to Partnership, and number of Partnership appointments, require more FTEs to prevent increases in wait times. In comparison, skillset demand changes and increases in no-show rates only required 0.5 additional FTE to mitigate resulting increases in wait times.

Chapter 6: Discussion

6.1 System Factors and Marginal Gains

In this paper we have demonstrated the impact of typically overlooked system factors on wait times. The two factors with the largest impact on wait times were percentage of clients continuing to Partnership, and the mean number of Partnership appointments per client. These two factors are integral to the performance of the system, yet may be less likely to be perceived by staff as having a significant effect on wait times. This may reflect an underestimation of the influence one's individual, day-to-day decisions could have on a larger system. As we have shown, adding FTEs, while a more visible intervention, may not be the most effective strategy for mitigating wait time; rather, small changes to individual decisions may better support the maintenance of benchmark wait times.

Delays in discharge or in transfer to lower intensity services contribute to increased mean numbers of Partnership appointments and represent prolonged use of resources with concomitant increases in wait times in many contexts, such as inpatient services and emergency departments [34]. In an outpatient context, there have been noted barriers preventing specialists from transitioning clients back to a primary care setting, where resources may be less scarce compared to a specialist setting [35]. This appears to be understudied in outpatient mental health literature, with most literature focusing only on client predictors for early withdrawal from treatment [36, 37].

The clinical determination of whether Partnership appointments are the best course of action to meet client needs may be influenced by the perception that transfer of care is not possible due to lack of services better suited to a client's needs. However, extending Partnership delays exit and thus slows the entry of new clients. A system with efficient flow will have a roughly balanced number of incoming and outgoing clients. A delay of exit will cause an imbalance of incoming/outgoing clients and cause substantial increases of waits. While much attention is paid to entry to services (i.e., the wait to Choice), the majority of the provision of care across the service occurs in Partnership. Thus, the accumulation of marginal gains from both the proportion continuing to Partnership, and overall number of appointments can cause large increases in wait times. These system factors are easily overlooked when examining methods to reduce wait times, but they were the two largest drivers of wait time increase in our study. Thus, our study shows that a series of seemingly minor changes in practice could reduce optimal client flow.

Another factor affecting clinics commonly mentioned in the literature, the rates of "no-shows", had a comparatively smaller effect on wait times to return in our study. This may be because the study clinic has a very low baseline no-show rate compared to other settings, stemming from intensive efforts by staff to reduce non-attendance, and the highest rate we tested represents a typical rate in other clinics [38, 39]. Therefore, our results may be conservative with respect to wait times in other settings. Regardless, our study shows the positive impact staff can have on system-level outcomes through their collective efforts to reduce non-attendance.

The system factors associated with the resource capacity of the clinic were the distribution of workload across staff (represented by skillset demand), and the number of FTEs at the clinic. Distribution of workload is eased by a staff compliment that can broadly offer the Core skills of CAPA. While providers may feel that they need to create the best match for a client, the trade-off between an optimal skillset match and wait times may mean that a marginally better client fit in terms of skills is compensated for by faster access.

6.2 Systems Thinking and Interdisciplinary Needs

Clinicians' day-to-day practices and decisions play an important role in wait times, and this is demonstrated through our results. Clinicians must strike a balance between individual care that meets clients' needs and providing timely access to a system that supports this care. The overall effect of all providers making minor changes may result in a large overall effect in the system, as demonstrated by this study. For example, adding just one more appointment for clients may seem to have little impact on the system, but we observed significant increases in waits when this practice was adopted clinic wide.

These individual decisions, when multiplied over an entire system, can create feedback loops. For example, adding an extra visit for the purpose of "checking in" prior to transferring out of the system contributes to increased wait times, which leads to reluctance by clients and families to leave the system for fear of long waits to re-enter should need warrant [8]. Clinicians are agents promoting clients' well-being when providing care. Of course, most clients in need are waiting before gaining access to services, and thus there is a countervailing need to operate efficiently to promote access for all. Demonstrating the system impact of small factors not only provides information for planning, but also highlights the importance of communicating the impact of decisions of individuals within the health system.

Readers are cautioned that simply pointing out that certain factors influence the system, does not necessarily mean changing that factor will always improve care. For example, a demand discrepancy may be an indication that there is not a full complement of staff, or that there is limited ability to transfer clients to more appropriate levels of care. This is a system issue, identified by the model, but solved through system changes that improve efficiency, and thus support client care. The ability to spot gaps and ask questions about the system demonstrates the utility of merging Operations Research with Health Services and clinical expertise to understand complex systems and support decision making in a clinical context; it provides the ability to make policy changes using techniques that provide evidence-informed decisions to support timely access to care.

Complex adaptive systems do not exist within a closed loop to outside systems, and pressures beyond CHMA services can have a large impact. The system parameters tested are concepts that can vary due to shifts in systems beyond CHMA, such as primary care, or services traditionally outside of health. For example, without access to primary care, a CMHA clinician may be more inclined to extend treatment to ensure appropriate follow-up; or a lack of specialist care may place more demand on CMHA services causing a higher proportion of clients continuing to Partnership services. Health systems are typically organized in silos, yet complex adaptive systems do not exist in these silos and therefore many complex interactions exist. The system factor variations selected are implicit to the potential changes caused by system-wide interactions and demonstrate the significant impacts.

The use of a simulation tool can inform planning decisions based on data driven techniques rather than budgetary approaches. A health services system has a responsibility to support clinicians in their practice through better use of resources. Systems thinking, incorporating an interdisciplinary approach, provides support to advocate for informed decision making, and the ability to view one's self in the overall system. A tool that captures system complexity, its interactions, and the potential outcomes is crucial to improving system understanding and planning. The guidance provided by the Knowledge-to-Action Cycle ensured the development of a useful, user-informed model, helped the research team learn about the system, and subsequently supported the use of the information to deliver results back to clinician staff, and gain insights into their role in a larger system.

This interdisciplinary approach undertaken by this study extends beyond shared understanding and communication. The development of a systems model requires many assumptions and simplifications to the system [29]. Having a team embedded within health services, supported by Operations Researchers allowed for a comprehensive elicitation of assumptions at the system level. These assumptions carried over into the data used to populate the model. The content experts' familiarity with these data sources, ensured assumptions about the data are valid. As is noted in the literature, both the model building process and study of results can guide stakeholders towards a broader understanding of systems thinking [20].

Using the insights gained from the process of model building, supported by integrated Knowledge Translation activities including the discussions of validation and the results from the model, supports evidence-informed decision making. The care delivery system is complex and thus it is difficult to estimate the outcome of a change in a system factor without the aid of a model. Results from operations research models enable providers to understand their contributions to the system, and the changes their practice can impart on system performance; the relative contribution of each system factor gives us an idea of how the current state may have happened, and therefore directions to reduce waits or mitigate further increase.

6.3 Limitations

As with any study, there are limitations that should be mentioned. First, the data from the Community Wide Scheduling (CWS) relies on accurate capture and collection of the appointments by providers at the clinic. Of course, errors can always be made when inputting this data, and there are limited processes in place to audit the quality of the data, as its primary purpose is administrative. We attempted to limit misclassification errors by using only Core Partnership appointments, which are clearly defined in the system, and straightforward in terms of the process. Further, the research did not rely on data for model validation, but rather to define a set of input parameters to act as a baseline configuration. The relative impacts of the various scenarios were the focus of the research, rather than prediction of the potential absolute changes.

A second limitation of the research is the lack of capture of clinical outcomes within the simulation. This research does not make any assumptions that decreasing wait times are inherently linked to better client outcomes, although there is literature to support timely access to mental health services results in improved clinical outcomes [40, 41]. Instead, we state the relative impact that clinic parameters can have on wait times. Communicating these relative effects to clinical staff was the goal of this research; their content knowledge can set the findings in the context of potential clinical outcomes.

Reporting of wait times also represent some limitations, and come with qualifiers for use and understanding. The client list, and data, for the simulation captures only those who have accessed services [42]. Therefore, we are missing those who did not access services, which may include individuals that have high need for mental health and addictions services. This is a difficult limitation to overcome, but warrants acknowledgement whenever using wait times as an outcome in health services research.

The last identified limitation of this research is the inability to capture heterogeneity across clients' presenting complaints and the associated differences in service use. There would likely be variation in treatment length, rates of no-show, and skillset demand based on the presenting complaint of a client, and not the conceptualization and quantification as a distribution as we have implemented in the model. We have chosen to use this approach as: 1) we did not have enough information to reliably capture variation in treatment, no-show rates, or skillset demand based on presenting complaint or diagnosis; and 2) when examining a clinic from the system level, the population-level approach can typically capture main system effects, and demonstrate the queuing relationships of a system [23].

6.4 Conclusions

The accumulation of marginal gains from the system factors, largely the number of appointments, and "continuing to Partnership", had the largest relative contributions to increasing wait times. This thesis has demonstrated the impact of five system factors on a steady state baseline system, and the relative contribution of each factor as they pertain to wait times. The implications of these findings extend beyond the outpatient mental health context, and more broadly into how decision makers conceptualize and communicate systems-thinking. The focus of reducing wait time often defaults to increasing capacity by adding more FTEs to a system, without first looking at practices already in place. It is clear that day-to-day decisions within a system can play a significant role on wait times.

These changes in system factors are often driven by systems beyond CMHA services, and it's clear that complex adaptive systems have a multitude of interactions that are difficult to capture. Demonstrating the impacts these complex interactions have, through variations in our system factors, we show potential for interplay between CMHA and other services, such as primary care. These complicated relationships are more readily communicated by using an interactive tool, such as DES modelling, which also acts as a framework for communication by many disciplines during the model building process. Evidence supplied by the model results provides the necessary insight to understand marginal gains, the potential system drivers behind them, and the capacity to plan using data-driven techniques.

To deliver high quality health care in a timely manner, there must be purposeful planning within a system, that responds to shifting inputs and system factors. It is necessary to make decisions on a reactive basis, yet decision makers must respond in a way that is evidence-informed and maintains function within the system. Understanding the system factors that contribute to increases in wait times, or the efforts required to mitigate them, aids in our ability to respond to shifting inputs and better adapt to changes [43]. The insights such as the results obtained provide a basis for system-thinking, and demonstrate the strength of interdisciplinary approaches to health services research. This research has provided a tool and results to inform planning through data-driven, and evidence-informed results, meanwhile quantifying the relative contribution a system factor has within the system.

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