An Industrial Engineering-Based Approach to Designing and Evaluating Healthcare Systems to Improve Veteran Access to Care

by

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Dedication

This work is dedicated to my teachers. Thank you for your guidance, instruction, and empathy. I will do my best to carry the torch.

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Abstract

Access to healthcare is a critical public health issue in the United States, especially for veterans. Veterans are older on average than the general U.S. population and are thus at higher risk for chronic disease. Further, veterans report more delays when seeking healthcare. The Veterans Affairs (VA) Healthcare System continuously works to develop policies and technologies that aim to improve veteran access to care. Industrial engineering methods can be effective in analyzing the impact of such policies, as well as designing or modifying systems to better align veteran patients' needs with providers and resources. This dissertation demonstrates how industrial engineering tools can guide policy decisions to improve healthcare access by connecting veterans with the most appropriate healthcare resources, while highlighting the trade-offs inherent in such decisions.

This work comprises four stages: (1) using optimization methods to design a healthcare network when introducing new provider options for chronic disease screening, (2) developing simulation tools to model how access to care is impacted when scheduling policies accommodate patient preferences, and (3) simulating triage strategies for non-emergency care during COVID-19, and (4) evaluating how treatment decisions impact patient access when guided by risk-based prediction models compared to current practice.

In the first stage, we consider veteran access to chronic eye disease screening. Ophthalmologists in the VA have developed a platform in which ophthalmic technicians screen patients for major chronic eye diseases during primary care visits. We use mixed-

integer programming-based facility location models to understand how the VA can determine which clinics should offer eye screenings, which provider type(s) should staff those clinics, and how to distribute patients among clinics. The results of this work show how the VA can achieve various objectives including minimizing the cost or maximizing the number of patients receiving care.

In the second stage, we simulate patients seeking care for gastroesophageal reflux disease with primary care and gastrointestinal providers. This simulation incorporates policies about how to schedule patients for visits in various modalities, including face-to-face and telehealth, and also considers uncertainty in key factors like patient arrivals and demographics. Results of these models can help us understand how scheduling based on these preferences impacts access, including time to first appointment and number of patients seen. Such metrics can guide healthcare administrators as new technologies are introduced that offer options for how patients interact with their providers.

In the third stage, we simulate patients seeking non-emergency outpatient care under reduced appointment capacity due to the COVID-19 pandemic. We demonstrate this using endoscopy visits as a central example. We use our simulation model to understand how various strategies for adjusting patient triage and/or clinic operations can mitigate patient backlog and reduce patient waiting times.

In the fourth stage, we integrate multiple industrial engineering methods to examine how access is impacted among chronic liver disease patients when predictive modeling is introduced into treatment planning. We developed a simulation model to help clinical decision-makers better understand how using a predictive model may change the care pathway for a specific patient and also impact system decisions, such as required staffing levels and clinical data acquired at specific patient visits. The model also helps clinicians understand the value of specific clinical data (lab values, vitals, etc.) by demonstrating how better or worse inputs to the predictive models have larger system impacts to patient access.

Chapter 1. Introduction

1.1. Motivation

Access to appropriate, affordable, and timely healthcare services is a major issue in the United States. Kullgren et al. (2012) showed that 29% of Americans reported having an unmet health need or delayed seeking care due to some barrier and 21% of those reporting access issues encounter nonfinancial barriers. (1) Access to healthcare was conceptually defined in 1981 by Penchansky and Thomas. (2) Prior to the Penchansky and Thomas definition, Aday and Anderson conceived of a relatively simple framework that solely considered socio-organizational and geographic dimensions of access. (3) Carrillo et al. (2011) created the Health Care Access Barriers (HCAB) model, which considers financial, structural, and cognitive barriers.(4) Kullgren et al. consider five dimensions – "affordability, accommodation, availability, accessibility, and acceptability" – in their framework. (1)

Access to care is especially challenging for patients with chronic diseases and patients living in rural areas, and can be further complicated by major public health challenges like the COVID-19 pandemic. (5) Regular access to care is especially important for the approximately 50% of the U.S. population who live with chronic diseases(s)/condition(s), as they typically need more regular interactions with healthcare systems. (6) Among people living with chronic diseases in the United States, over 50% have experienced challenges accessing healthcare. (7) Further, compared to those living in urban or suburban areas, people living in rural areas are more likely to live geographically far from a healthcare provider, report fair/poor health, access healthcare less frequently, and have one or more chronic conditions. (8–11)

Preventive care, including screening, is important to reduce morbidity and mortality of chronic disease. Such care is provided by highly trained medical providers, such as licensed physicians, physician assistants, or nurse practitioners. Additional resources used for such preventive care may also include specialized equipment and testing. These resources, both personnel and equipment, contribute to meaningful care, but are often expensive. Further, such specialized resources come with additional logistical challenges: they may be difficult to place in rural areas, they may consume a large amount of physical space, and/or a shortage of such resources may exist (e.g., provider shortage).

In this work, we will explore how industrial engineering tools can be used to evaluate and design aspects of healthcare systems to improve access, with a focus on access to care for United States veterans. Veterans typically receive healthcare at Veterans Health Affairs (VHA) clinical locations. As a subpopulation, veterans have several characteristics that can make accessing healthcare challenging. The VHA also has several unique organizational components that distinguish it from other healthcare providers, making policy and operational changes more amenable to evaluation using engineering methodologies.

1.2. Engineering Tools for Evaluating Access to Healthcare

Engineering tools can help identify and propose solutions to resolve barriers to care by more effectively allocating limited resources, including facilities and personnel, and by incorporating new services and technologies when modeling access. Models vary based on the dimension of access they are targeting, ranging from spatial interaction models to measure geographic healthcare access, (12) integer programming models to address patient appointment scheduling, (13) and basic statistical and economic models to analyze financial access. (13,14)

Facility location models were introduced by Alfred Weber in 1929 and were applied to healthcare problems in later decades. (15) Facility location problems can be applied to several problems in healthcare, including ambulance dispatching and routing, blood bank locations, and emergency care services planning. Examples of facility location models applied to access are include considering how to locate clinic buildings and/or services to minimize the average distance that patients travel for a medical visit or determining the minimum number of facilities needed to satisfy patient needs within a geographic area.

Mehrez et al. (1996) describe a model with a single facility optimization, which allows them to evaluate four different objective functions and problem structures. (16) In their paper, which considers where (and whether) to build a hospital in a finite set of locations in southern Israel, the authors first evaluate models using iterative scenario analyses and then qualitatively examining model results using multi-criteria hierarchical analysis software. This paper clearly outlines the sociopolitical challenges related to healthcare access, including issues with government support, community-based social norms, and public security. Additionally, constraints are clear and reasonable. The authors' inclusion of Euclidean distance analyses in some of their models may oversimplify their research question, however their use of more precise distance measurements in two of the four models alleviates this issue to an extent. The major takeaway of this paper is the methodology for including subjective information in a facility location model, specifically when implementing a new provider facility.

In her 2011 paper, Nicoleta Serban discusses service accessibility equity using a space-time varying coefficient model. (17) Here, her focus on access is primarily geographic, but travel logistics are also considered. She accurately notes the challenge in measuring individual travel costs for a specific community. The model itself is a multilevel varying coefficient model that considers services providers which interact between time and space. Though such a model may be burdened by issues with computational efficiency, Serban utilizes penalized splines and an inference procedure for assessing the space-time varying coefficients. Serban applies her model to equity of utilization of financial services, stratified by race and income. This paper contributes to the literature through its methodology for addressing computational efficiency of a multilevel space-time varying coefficient model, as well as its inclusion of a simulation study to confirm model estimation.

A 2005 paper by Wang and Luo adds to their two-step floating catchment area (2SFCA) method, first introduced in 2003. (18,19) The original 2SFCA paper considers includes both (a) provider supply in a given area, and (b) where the population is situated – effectively a ratio of provider-to-population. In their 2005 paper, the authors focus on how this approach can be used to address "health professional shortage areas" – geographical regions that have been designated as medically underserved. Such areas are often rural. In addition to the spatial measurements provided by 2SFCA, the authors also incorporate nonspatial variables via factor analysis. They integrate both aspects to indicate healthcare needs in a given geographical area. While their 2003 paper was effective in defining a critical metric (2SFCA) the 2005 paper is an appropriate and meaningful addition that considers basic population demographics to more wholly indicate healthcare needs.

Tang et al. (2017) expand on the 2SFCA method by incorporating spatial patient flows that model human decision behavior, including an individual's (nonspatial) healthcare needs. (12) They demonstrate their model using a case of elderly patients in Taipei City accessing general practitioner services. They compared their enhanced model (dubbed "F2FCA") with the original 2FSCA model, as well as two intermediate models that include capacity of services and an exponential distance-decay function. The authors' F2FCA model is a needed improvement on earlier geospatial analysis that focus primarily on geographic relationships between providers and patients while minimizing the importance of other aspects of access.

In their 2013 paper Mao and Nekorchuk also consider an expansion to the 2SFCA method by incorporating multiple transportation modes. (20) While traditional geospatial models typically assume a single transportation mode, Mao and Nekorchuk alleviate this irrational assumption by stratifying by sub-populations who use varying transportation modes. They illustrate their model using a case study of hospitals in Florida. Papers that consider multiple transportation modes for healthcare access are rare, so the work of Mao and Nekorchuk is certainly meaningful. Further, their paper highlights a need for more sophisticated transportation data and simulation analysis methods related to transportation modes. Nevertheless, their assumptions about how individuals choose transportation modes based on distance from a provider are both over-simplified and ignore patients who would negate care due to not having an available feasible transportation mode.

Fahui Wang adds to his earlier contributions in developing the 2SFCA with a 2012 review paper on optimization methods in healthcare access. (21) Key models reviewed include the p median problem, which seeks to minimize total travel distance or time, the location set covering problem (LSCP), which seeks to minimize the number of facilities needed to cover demand, and the center model, which seeks to minimize the maximum distance to cover all individuals. Such models each have their pros and cons, and Wang encourages the reader to understand what type of model will suit their problem most appropriately.

Aside from facility location models, one of the most common applications of operations research (OR) across all industries is scheduling and this norm holds in the healthcare industry, especially in patient appointment scheduling. In their 2008 paper, Gupta and Denton provide an overview of appointment scheduling as an application of OR. (22) Notably, they identify four key variables that influence the performance of patient appointment models: (a) mapped arrival processes, (b) service processes, (c) patient and provider preferences, and (d) incentives and performance measures. While the former two variables are often considered in OR applications through probability distributions and/or sensitivity analyses, the latter two variables are both meaningful and can be relatively specific to the healthcare industry. Gupta and Denton conclude their paper with several opportunities for future work. One such opportunity is health system design. While this paper is over ten years old, health system design is still relevant today. Since this paper was published, the United States has adopted the Patient Protection and Affordable Care Act (the "ACA"), which proposes significant changes to provider reimbursement and patient insurance coverage – both of which impact health system design. While the ACA was under fire from an oppositional federal government during the Trump administration, it appears to be more likely to remain intact for the foreseeable future. (23) Nevertheless, there is uncertainty involved when designing and/or modifying health system structures, so OR tools are likely to remain relevant for addressing system design moving forward.

In a 2017 paper, Matthias Schacht proposes a reconfiguration of appointment systems to improve same-day access for primary care appointments. (24) Schacht uses a stochastic mixed-integer linear program to aid in the development of weekly schedules in a primary care clinic. Schacht is particularly interested in understanding how seasonality affects the stochasticity of patient arrivals for same-day appointments. He proves his model successful in a case study, however the proposed model is burdensome to arrange for a given period and the administrative effort in implementing and sustaining such a model seems daunting. While Schacht's methodological approach provides a new perspective, his paper reminds the reader to consider the realistic expectations of applying OR models to address healthcare access.

The previous scheduling papers focus on more general or primary care appointments, but a 2016 paper by Castaing et al. discusses a specialized application of stochastic programming to reduce patient wait times in outpatient infusion centers. (25) Such appointments have highly variable lengths, a feature which requires uncertainty to be incorporated into model development and analysis. The authors develop a stochastic program of a Schedule Refinement Optimization Problem (SROP), as well as heuristic algorithms for approximating the SROP and schedules to allow cancer center staff to adjust preferences for patient wait times and staff idle time. They apply their SROP to an outpatient infusion center to evaluate the necessary number of simulated scenarios and to compared schedules. This paper appropriately considers the externalities of efforts to improve patient access, namely operational effects on staff and resources. While their model simplifies the infusion center processes, the granularity is appropriate for such an application.

While general scheduling methodologies (linear/integer programming, etc.) remain somewhat consistent throughout the literature, applying those methodologies tends to require individualization on a deeper, and not necessarily obvious, context compared to applications of facility location models. While facility location models clearly require geography-specific updates when applying to different areas, scheduling problems often require the incorporation of organizational policies, staffing requirements, and other operational constraints for them to be meaningful.

OR can also be used in considering financial access to care. The first chapter of *Operations Research and Health Care Policy* (2013), written by Rauner and Scaffhauser-Linzatti, discusses inpatient reimbursement systems in Austria. (26) In 1997, the Austrian national healthcare system replaced a day-based payment structure for inpatients with a case-based system similar to those used with diagnosis-related groups (DRGs). The authors discuss optimization methods used to ensure the case-based system operates effectively. Optimization models are routinely run to monitor patient length-of-stay guidelines and hospital patient mix and volumes. Additional nonlinear optimization models are used to allocate variable budgets to optimize patient quality outcomes and discrete-event simulation is used to demonstrate competition of hospitals under case-based versus day-based payment systems. While the authors themselves did not conduct all of these studies, this suite of OR tools helps policymakers comprehensively understand the impact of their recently-adopted payment system.

In another chapter, Zaric et al. model risk sharing agreements (RSAs). (27) While their models focus primarily on RSAs among pharmaceutical manufacturers and insurance companies in single-payer health systems, RSAs are becoming increasingly common between providers and patients in multi-payer systems (such as the United States). In such agreements, patients are typically held more financially accountable for their health and associated healthcare costs. This shift of risk onto patients and/or their insurers is intended to incentivize patients to make more informed and appropriate healthcare decisions, especially as providers are seeing decreasing reimbursement schedules under the ACA. OR tools, such as optimization and risk analysis methods, can be effective in analyzing the impact of RSAs on the larger healthcare system.

Previous research analyze access using engineering tools typically focus on one dimension of access (location, scheduling, etc.), but some work does attempt to incorporate multiple dimensions. Luo and Wang (2003) attempt to address multiple components of access with the 2FSCA approach, later built upon by Tang et al. (2017) and Mao and Nekorchuk (2013). (12,18,20) Nevertheless, these models do still miss components of access, including financial/insurance policy aspects.

Policy changes can have broad impact on health system access. Simply adding more providers or offering different appointment times does not necessarily allow more patients to access care. Further, policy changes may have unintended downstream or systemic effects, especially when considering long-term treatment and precision health components. This work intends to more fully understand how policy changes systematically impact to access to care and how systems engineering methods can be employed to develop this understanding.

1.3. The Veterans Health Administration

The United States Department of Veteran Affairs (VA) is a federal agency with three administrations: the Veterans Health Administration (VHA), the Veterans Benefits Administration, and the National Cemetery Administration. The VHA provides healthcare for eligible veterans. Veterans are eligible for VHA care if they previously served in active military service and were not dishonorably discharged. Additional eligibility requirements based on time of service and household income also apply. Individuals who previously served or are currently serving in the Reserves or National Guard and completed a full period of active duty are also eligible.

The VHA is geographically organized into 18 Veterans Integrated Service Networks (VISNs), which manage care delivery in a region. Each VISN oversees several VHA medical centers (VAMCs) and community-based outpatient centers (CBOCs), as well as Community Living Centers (CLCs). VAMCs offer two or more types of care including inpatient, outpatient, residential, and institutional extended care, while CBOCs provide outpatient services. (28,29)

Unlike most other healthcare providers in the United States, the VHA is an integrated health system with a single payer; the federal government provides all VHA funding. This distinction can enable the VHA to encourage access to care, especially preventive care. By focusing resources on preventive care, the VHA will not only provide more proactive care for its patients, but it can also mitigate future higher costs of care. For example, the VHA is motivated to thoroughly screen cancer patients for malignancy so that any cases can be treated early, when tumors may be more easily – and cheaply – treated. Non-VHA providers are compensated based on volume of treatment, with more complex treatment often more highly compensated, and are thus less motivated to pursue preventive care.

Compared to the general United States adult population, veterans are older; 48.8% of veterans are aged 65+ compared to 16.5% in the general population. (30) Veterans also are more likely to have chronic conditions, with 25.5% reporting one chronic condition and 47.9% reporting two or more (a total of 73.4%). (31) For comparison, the general US adult population has 18% of people reporting one chronic condition and 42% reporting two or more. (32) Further, veterans experience greater delays in accessing healthcare than non-veterans. (33–35) The combination of high risk for chronic disease and challenges in accessing care makes *how* care is provided to veterans an important consideration.

1.3.1. Recent Congressional Acts Impacting Veteran Access

The United States Congress passed the Veterans Access, Choice, and Accountability Act in 2014. (36) This law set several national rules related to veterans' access to care, including requiring that covered veterans receive a medical appointment within 30 days of request and that patients should not travel more than 40 miles to reach a VHA clinic for medical care. If care cannot be provided to a covered veteran within these and other access-related requirements, the patient may choose to seek care from a medical center outside of the VHA. This Act also stipulates that any follow-up care within 60 days of an initial visit can be provided by the same medical provider. While this measure is helpful to ensure continuity of care, this continuity is myopic; it is helpful to improving quality of care only in the short-term.

In 2018, Congress passed the VA MISSION Act. (37) Several rules in the MISSION Act impact the work presented herein. This work adds to the requirements outlined in the 2014 Access, Choice, and Accountability Act by providing funding specifically for non-VHA medical care ("community care") that patients may utilize, as well as ensuring those visits are paid for by the VHA. Through this and other measures that provide funding for community care facilities outlined in the MISSION Act, veterans have more options when choosing where to receive care.

The Veterans Access, Choice, and Accountability Act and MISSION Act improve veteran access to healthcare by lowering geographical, temporal, and logistical barriers. One may also argue that financial barriers are minimized because the cost of community care services are covered under the MISSION Act, however veterans should theoretically see no difference in the amount paid out-of-pocket if they were currently using the VHA for care. However, these acts degrade one of the chief advantages of the VHA: continuity of care, particularly in longitudinal care. While the acts do contain stipulations requiring sharing of patient information between VHA and community providers, patients lose the integration of services and institutional knowledge that comes with continuous care within one system.

One solution, as indicated in the work of this dissertation, is to encourage use of VA medical services by distributing internal resources in ways that improve access for veterans and ensure that veterans can receive meaningful care. If, instead of providing financial coverage for non-VHA providers, the VHA uses its own personnel and other resources more efficiently, more veterans can maintain their care from within the VHA.

1.4 Dissertation Summary

This work comprises four stages: (1) using facility location and other optimization methods to design a healthcare network when introducing new provider options for chronic disease screening, (2) developing simulation tools to model how access to care is impacted when scheduling policies accommodate patient preferences, (3) evaluating triage strategies under COVID-19-related capacity restrictions, and (4) determining how treatment decisions impact patient access when guided by risk-based prediction models compared to current practice. Through these stages, we illustrate how industrial engineering can be used to understand impact on veteran healthcare access when new policies or operations are considered.

1.5. Key Contributions

In Chapter 2 we demonstrate a mixed-integer program to show how the VHA can distribute providers for eye care screening within a VISN to maximize the number of patients seen. This work considers an innovative form of care delivery – technology-based eye care screenings (TECS) – and demonstrates how the VHA can scale this service to improve patient access for chronic disease screening. This model can serve as a framework for the VHA as they consider new technologies, policies, and venues for care delivery.

In Chapter 3 we show how patient preference for appointment modality (in-person versus telehealth) can be considered with minimal impact to health system operations or patient outcomes for VHA patients with gastroesophageal reflux disease. While our case study indicated no negative outcomes to patient access or clinic operations, the simulation model could be applied to other diseases, clinic locations, and/or patient populations to understand the impact of considering such patient preferences, especially as healthcare providers across the country embrace more care provided via telehealth.

In Chapter 4 we present a simulation model to guide VHA clinics providing non-emergency outpatient care as they triage patients under reduced capacity due to the COVID-19 pandemic. This model was developed using the Ann Arbor, Michigan VHA endoscopy clinic as a case study, but has been applied to other VHA endoscopy clinics across the country. Further, while the model is designed to guide clinical decision-makers in how to best allocate their limited capacity during a pandemic, the model can also be used to better triage patients by urgency of need during non-pandemic times.

Finally, in Chapter 5 we consider how the inclusion of new data-driven models impacts patient access for chronic liver disease patients. Machine learning and other predictive modeling tools have the potential to improve the accuracy of diagnoses and enhance the personalization of treatment plans, but little work has been done to indicate how including such advanced models in a care pathway may impact access. Our simulation model demonstrates this impact, with consideration for patient outcomes.

Chapter 2. Improving Veteran Access to Screening for Chronic Eye Disease

2.1. Introduction

Preventive care, including screening, is important to reduce morbidity and mortality of chronic disease. Such care is provided by highly trained medical providers, such as licensed physicians, physician assistants, or nurse practitioners. Additional resources used for such preventive care may also include specialized equipment and testing. These resources, both personnel and equipment, contribute to meaningful care, but are often expensive. Further, such specialized resources come with additional logistical challenges: they may be difficult to place in rural areas, they may consume a large amount of physical space, and/or a shortage of such resources may exist (e.g., provider shortage).

In many cases, a lower cost, more abundant resource can be used initially in place of higher cost, more constrained resources. For example, as we present in this chapter, ophthalmic technicians can screen veteran patients for chronic eye diseases within a telemedicine structure. Such screenings were often previously performed in-person and only by ophthalmologists or optometrists. When technicians instead screen these patients through telemedicine modalities, the Veterans Health Affairs (VHA) system benefits by reducing cost per screening, while having the additional benefit of locating technicians at a greater number of clinic locations than would be feasible from cost and space perspectives with only ophthalmologist- and optometrist-conducted in-person screenings.

In this chapter, we present a mixed-integer program that considers how screening for chronic eye disease is provided in VHA clinics. In particular, we consider how to locate ophthalmic technicians and other eye care providers to maximize the number of patients screened for eye disease within the VHA, subject to a given budget, or minimize system costs, subject to a required number of patients who must be screened within the VHA. We also discuss how this model could be applied more broadly when health systems are evaluating how to improve patient access for chronic disease care by using various provider types.

2.2. Background: Chronic Eye Disease Screenings for Veterans

2.2.1. Chronic Eye Disease

Over 1 million adults in the United States are legally blind and approximately 3.2 million U.S. adults are visually impaired. Furthermore, prevalence of blindness and visual impairment are expected to double by 2050. (38) Blindness and visual impairment affect an individual's life by making daily tasks like driving more challenging and also increasing risk for injuries and falls. (39) Blindness and visual impairment also have an economic impact. As stated in a 2007 report on the economic impact of vision problems in the U.S., "the total excess monetary impact of visual impairment and blindness, attributable to medical and informal care, is estimated at $5.48 billion annually." (40)

The leading causes of blindness in the U.S. are primarily chronic eye diseases including cataract, glaucoma, age-related macular degeneration, and diabetic retinopathy. (41) A common risk factor among all of these diseases is age; as a person gets older, their risk for these diseases increases. Another common risk factor for chronic eye disease is the presence of systemic medical condition such as diabetes or hypertension. (42) Each of the four diseases mentioned affects demographic groups differently but all can be treated by optometrists and ophthalmologists. Each disease also progresses uniquely, but earlier detection typically leads to better outcomes. (43) Because early detection can lead to better outcomes, access to timely and geographically proximate screening is critical, especially for patients at higher risk for chronic eye disease.

Diabetes is strongly associated with vision impairment and other non-diabetic eye disease. (44) Patients in Veterans Health Administration (VHA) clinics have higher prevalence (11.4%) of diabetes compared to the general United States population (7.2%) and are also older (48.8% aged 65+), and thus VHA patients are at higher risk of chronic eye disease. (30,45) Further, veterans may experience greater delays in accessing healthcare than non-veterans as eye care is the third most-utilized service in the VHA and rapidly growing. (33–35) The combination of high risk for eye disease and challenges in accessing eye care makes *how* eye care is provided to veterans an important consideration.

2.2.2. Veteran Eye Care and the TECS Program

Many United States veterans receive their general healthcare from their primary medical care home, a VHA primary care clinic location, otherwise known as Community Based Outpatient Clinic (CBOC). When veteran patients visit VHA facilities, the veterans do not pay out-of-pocket for care, with some exceptions. Patient records are connected across VHA clinics through an electronic medical record system and clinics are also connected monetarily via a capitated system with a limited budget to care for veterans' needs. (46,47) Because of this integration, clinicians may be cost-incentivized to provide high-quality care, especially preventative care, regardless of location.

As the largest healthcare system in the United States, the VHA utilizes a wide variety of telehealth modalities for patient care. The Technology-based Eye Care Services (TECS) program began in 2015 at the Atlanta VHA, the largest and one of the most complex VHA hospitals in the state of Georgia. The Atlanta VHA is part of Veterans Integrated Service Network (VISN) 7, which covers the Southeast (Alabama, Georgia, South Carolina) United States region. TECS is a comprehensive tele-eye screening program in which highly-trained ophthalmic technicians perform visual disease screenings for veteran patients in a CBOC. These screenings are usually performed in conjunction with a patient's primary care visit. After the screening, optometrists and ophthalmologists remotely review digital ophthalmic photographs from the screening and provide screening assessments. If patients screen positive for disease, they are referred for follow-up care via face-to-face examination with an ophthalmologist or optometrist, usually in the VHA system. The TECS program has been deemed medically effective and of high clinical quality. (35)

2.2.3. Designing a Network for Veteran Eye Screening

VISN 7 has begun implementing the TECS program and currently has technicians screening patients at ten CBOCs across 2 states – Atlanta, GA; Tifton, GA; and Montgomery, AL. The decisions about where to place the first technicians were determined largely by considering pre-existing CBOC locations where patient demand existed but the VA could not feasibly locate an optometrist or ophthalmologist either due to space, geographic, or hiring constraints. These initial placements were also helpful in demonstrating efficacy of the TECS program.

Moving forward, systems engineering models may be helpful to the VHA as decision-makers consider where to add additional technicians in the region and/or where to launch the TECS program in other areas of the country. Such models can help the VHA meet various objectives for eye care delivery, including maximizing the number of patients seen or minimizing costs, while ensuring access, quality, and administrative guidelines are followed.

Some trade-offs to consider when designing a network for the TECS program are relatively straightforward. For example, adding a technician at a rural clinic location will increase system costs, but will increase the number of patients able to be screened and will also likely reduce the distance patients travel for screening. Additionally, more complex trade-offs should be considered, including a provider's patient mix. As technicians are added to the network, they can screen patients, including patients previously screened by ophthalmologists and optometrists and new patients who would not have previously been screened. However, the screenings create a referral into the system which needs to be considered. Another trade-off is that with TECS, ophthalmologists and optometrists may screen fewer patients, but can treat more patients with complex care needs, by ophthalmic surgery or disease management.

2.3. Systems Engineering Models for Veteran Eye Screenings

Using data from VISN 7, we developed integer programming models to design TECS networks in Georgia. These models were developed in collaboration between systems engineers and VHA clinical administrators. Each model has an objective function, decision variables, and constraints. The objective function indicates a value we are attempting to minimize or maximize by changing the values of the decision variables. The constraints indicate rules we must follow as we are changing those decision variables. Two models are discussed in greater detail in the next paragraphs. Models were coded in C++ and solved using CPLEX Optimization Studio.

We focus on two models for this chapter – one in which our objective function maximizes the number of patients we can screen within the VHA, subject to a fixed budget (Model A), and another in which the objective is to minimize total costs, subject to a given number of patients required to be screened in the VHA (Model B). Table 1 outlines model details. Note that other objective functions could be used when considering designing a TECS network, such as minimizing the average distance patients travel to get to a clinic location.

Table 1. Overview of Mixed-Integer Programming Models to Improve Veteran Access to Eye Care

<table>
<tr><th></th><th>Model A</th><th>Model B</th></tr>
<tr><td>Objective</td><td>Maximize the number of patients screened in the VA</td><td>Minimize costs</td></tr>
<tr><td>Decision Variables</td><td colspan="2">Where to provide eye care, what type(s) of providers at each location, and how patients from given zip codes are “assigned” to clinic(s)</td></tr>
<tr><td rowspan="6">Constraints</td><td>Budget</td><td>Required number of patients screened in the VA</td></tr>
<tr><td colspan="2">Allowed travel distance between patient zip code and assigned clinic</td></tr>
<tr><td colspan="2">Allowed travel time between patient zip code and assigned clinic</td></tr>
<tr><td colspan="2">Capacity of each location for total number of providers</td></tr>
<tr><td colspan="2">Capacity of each location for number of providers of a given type</td></tr>
<tr><td colspan="2">Provider capacities on number of patients screened per time period and minimum percent capacity used</td></tr>
<tr><td></td><td colspan="2">Required percentage of patients from each zip code required to be screened</td></tr>
</table>

In each of these models, the decision variables indicate at which VHA clinic locations providers should be placed, what type(s) of and how many providers should be at each location, and the clinic location(s) to which patients from each zip code are assigned. If patients are not assigned to a VHA clinic, we assume they seek care from a non-VHA community provider. Model sets, parameters, and decision variables are outlined as:

Sets

- ***Z***: a set of zip codes, *z*, each with a geographic location, a non-zero integer population of veteran residents, and a set of distances to each of the candidate clinic locations

- $\boldsymbol{C}$: a set of candidate clinic locations, *c*, each with a geographic location and a set of distances to each zip code
- $\boldsymbol{T}$: a set of the types of eye care providers, *t*, who can staff a clinic (***t***=1 indicates an ophthalmologist, *t*=2 indicates an optometrist, *t*=3 indicates a technician), and a capacity (the number of patients that a specific provider type can see annually)

Parameters

- $\boldsymbol{b}$: budget, in United States dollars
- $\boldsymbol{n^l}$: a lower bound on the percentage of patients that must be assigned to in-system screening from each zip code
- $\boldsymbol{n^u}$: an upper bound on the percentage of patients that must be assigned to in-system screening from each zip code
- $\boldsymbol{r}$: per mile reimbursement amount for patient travel, in United States dollars
- $\boldsymbol{m}$: the furthest distance from a zip code to a clinic that patients are allowed to travel
- $\boldsymbol{s}$: the furthest time from a zip code to a clinic that patients are allowed to travel
- $\boldsymbol{q}$: the minimum number of total patients screened across all zip codes
- $\boldsymbol{j}$: a lower bound on provider utilization, $0 \leq j \leq 1$
- $\boldsymbol{D_{zc}}$: a set of travel distances, d_{zc}, between zip code *z* and candidate clinic location *c*, $\forall\ c \in C, \forall\ z \in Z$
- $\boldsymbol{T_{zc}}$: a set of travel times, t_{zc}, between zip code *z* and candidate clinic location *c*, $\forall\ c \in C, \forall\ z \in Z$
- $\boldsymbol{P_z}$: a set of populations, p_z, of veteran residents in each zip code, *z*, $\forall\ z \in Z$
- $\boldsymbol{V^t}$: a set of patient capacities, v^t, that provider type *t* can see annually $\forall\ t \in T$

- $\boldsymbol{A_c^t}$**:** a set of annual care costs, a_c^t, for a provider type *t* to screen a patient at clinic *c*, $\forall\ c \in C, \forall\ t \in T$
- $\boldsymbol{E_z}$: a set of flags, e_z, to indicate a zip code, *z*, is beyond the maximum allowable distance, *m*, or maximum allowable time, *s*, from any candidate clinic location. If true, $e_z = 1$, otherwise $e_z = 0,\ \forall\ z \in Z$
- $\boldsymbol{F_c^t}$**:** a set of per-provider costs, f_c^t, to hire a provider type *t* to screen patients at clinic *c* for one year, $\forall\ c \in C, \forall\ t \in T$
- $\boldsymbol{G_c^t}$**:** a set of upper bounds on capacity, g_c^t, of provider type *t* at clinic *c*, $\forall\ c \in C, \forall\ t \in T$
- $\boldsymbol{G_c}$**:** a set of upper bounds on capacity, g_c, of the total providers at clinic *c*, $\forall\ c \in C$

Decision Variables

- $\boldsymbol{w_{z,c}^t}$: the number of patients from zip code *z* to visit provider *t* at clinic location *c*, $\forall\ c \in C, \forall\ t \in T, \forall\ z \in Z$
- $\boldsymbol{y_c^t}$: the number of providers of type *t* to staff clinic location *c*, $\forall\ c \in C, \forall\ t \in T$

Several constraints are used in both models, including a limit on driving distance/time for patients, each provider type's capacity for patients (with a lower-bound on capacity used), and each clinic location's capacity for providers. To ensure patients from rural zip codes are considered appropriately, we also add a constraint that requires a minimum percentage of patients from each zip code who must be screened in the VHA. These constraints and objective functions are outlined mathematically as:

Constraints

Patient Capacity Requirement

$$j^t * v^t * y_c^t \leq \sum_{z \in Z} w_{z,c}^t \leq v^t * y_c^t \quad \forall\, c \in C, \forall\, t \in T$$

Demand Requirement

$$n^l * p_z \leq \sum_{c \in C} \sum_{t \in T} w_{z,c}^t \qquad e_z = 0, z \in Z$$

$$0 \leq \sum_{c \in C} \sum_{t \in T} w_{z,c}^t \qquad e_z = 1, z \in Z$$

$$\sum_{c \in C} \sum_{t \in T} w_{z,c}^t \leq n^u * p_z \qquad \forall\, z \in Z$$

Provider Capacity Requirement

$$y_c^t \leq g_c^t \qquad \forall\, c \in C, \forall\, t \in T$$

$$\sum_{t \in T} y_c^t \leq g_c \qquad \forall\, c \in C$$

Furthest Traveling Distance/Time Requirements

$$\sum_{t \in T} \sum_{z \in Z} \sum_{c \in C_{d_{z,c} > m}} w_{z,c}^t = 0$$

$$\sum_{t \in T} \sum_{z \in Z} \sum_{c \in C_{t_{z,c} > s}} w_{z,c}^t = 0$$

Budget Requirement (Model A only)

$$\sum_{c \in C} \sum_{t \in T} \sum_{z \in Z} \left[\left(a_c^t + r * d_{z,c} \right) * w_{z,c}^t + f_c^t * y_c^t \right] + h * \sum_{z \in Z} \left(n^u * p_z - \sum_{c \in C} \sum_{t \in T} w_{z,c}^t \right) \leq b$$

Minimum Number of People Screened In-System Requirement (Model B Only)

$$\sum_{c \in C} \sum_{t \in T} \sum_{z \in Z} w_{z,c}^t \geq q$$

Objective Functions

Model A

Maximize $\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z} w_{z,c}^{t}$

Model B

Minimize $\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z}[a_c^t * w_{z,c}^t + \left(r * d_{z,c} * w_{z,c}^t\right) + f_c^t * y_c^t] + h *$

$\sum_{z\in Z}\left(n^u * p_z - \sum_{c\in C}\sum_{t\in T} w_{z,c}^t\right)$

The model constraints reflect VHA administrative requirements, as well as goals for improving access to care. However, our base models primarily require that patients are assigned to clinics that are (a) open/have capacity and (b) are within the required driving distance/time from their home. Thus, patients may be assigned to a clinic that is 35 miles from their home, when another clinic 10 miles from their home also provides eye disease screening. To account for this, we have conducted an additional analysis that considers patient behavior by including constraints that indicates patients must visit the closest open clinic; that is, a patient is assigned to whatever clinic location is both open and has the shortest distance from the patient's home zip code. We demonstrate the updates to our model formulation required for this scenario in the following proof:

Nearest Clinic Requirement Model Update and Proof

Claim. In our previously established mixed-integer program, we decide which clinics should offer eye care, what provider type(s) should staff each clinic, and how patients from zip codes are assigned to each open clinic. We previously considered *C* clinics and *Z* zip codes. We now consider for each zip code, z, an ordered set of clinics, C_z^*, with each clinic denoted by c_z^i. These clinics are ordered such that clinic c_z^1 is the closest clinic to zip code z, clinic c_z^2 is the second closest clinic, etc. We assume no clinics are equally distant from a given zip code (that is, no "ties" exist in ordering clinics). The variable y_c indicates if clinic c is open (where a value of 1 indicates the clinic is open) and the variable $x_{z,c}$ indicates if patients from z are assigned to c. To ensure patients are assigned to the nearest open clinic, we add the following constraints to our previously established model:

(1) $x_{z,c_z^i} \leq y_{c^i}, \forall z \in Z, \forall c_z^i \in C_z^*$

(2) $\sum_{c_z^i=1}^{C_z^*} x_{z,c_z^i} = 1, \forall z \in Z$

(3) $\sum_{c_z^j=c_z^{i+1}}^{C_z^*} x_{z,c_z^j} \leq \left(1 - y_{c^i}\right), \forall z \in Z, \forall c_z^i \in C_z^*$

Constraint (1) requires patient zip codes only be assigned to a clinic that is open. Constraint (2) requires that each patient zip code is only assigned to one clinic. Constraint (3) requires that patient zip codes are assigned to the nearest *open* clinic.

Proof. By contradiction: Suppose there exists a zip code z with patients assigned to (open) clinic k. Suppose there also exists some clinic, l, which is also open and closer to z than clinic k.

1. By supposition and constraints (1) and (2):

$$x_{z,k} = 1, x_{z,l} = 0, y_k = 1, y_l = 1$$

2. Because all $x_{z,c}$ variables are binary by constraint (3):

$$x_{z,k} \leq \sum_{i=l+1}^{k-1} x_{z,i} + x_{z,k} + \sum_{i=k+1}^{C_z^*} x_{z,i}$$

   And also by constraint (3):

$$\sum_{i=l+1}^{k-1} x_{z,i} + x_{z,k} + \sum_{i=k+1}^{C_z^*} x_{z,i} \leq (1 - y_l)$$

Thus:

$$x_{z,k} \leq (1 - y_l)$$

$$1 \leq (1 - 1)$$

$$1 \leq 0$$

which cannot be true.

Given the added constraints, if zip code z is assigned to a clinic, but another clinic is open and closer, the constraints will be violated.

Finally, we have developed an extension of Model A that considers both screening and follow-up care (Model A+). In Model A+, some percentage of patients require additional appointments (follow-up care), indicating they have screened positive for some chronic eye disease. The additional appointments incur both costs and appointment capacity of optometrists and ophthalmologists; technicians cannot provide follow-up care. To incorporate follow-up care, we solve two consecutive mixed-integer programs (MIPs). The first MIP is structured the same as Model A, which maximizes the number of patients screened, subject to a budget. Under Model A+, the budget in this first MIP is reduced to reflect that some patients will require follow-up care and thus the entire budget should not be allocated to screening patients. The second MIP is structured similarly to Model A, but now maximizes the number of patients who receive follow-up care. In this second MIP, we add a constraint that we must screen at least N patients, where N equals the objective function of the first MIP. We also adjust constraint values to reflect the capacity and costs of both screening and follow-up care.

When considering the mathematical notation of Model A+, we broadly consider ρ, the probability that a patient screens positive for some chronic visual disease, and τ, the additional number of treatment appointments that a patient would need if screened positive. We assume (a) that all positive-screened patients require the same number of treatment appointments, (b) that all patients go to treatment appointments when there is appropriate capacity, (c) optometrists and ophthalmologists are both qualified/licensed to treat all chronic visual disease, and (d) that capacity inputs for optometrists and ophthalmologists are updated to include both their screening and treatment capacities (previously capacities only included screening). We update our patient assignment decision variables to include:

- $\boldsymbol{w_{z,c}^t}$: the number of patients from zip code *z* to visit provider *t* at clinic location *c* for screening, $\forall\, c \in C, \forall\, t \in T, \forall\, z \in Z$
- $\boldsymbol{k_{z,c}^t}$: the number of patients from zip code *z* to visit provider *t* at clinic location *c* for treatment, $\forall\, c \in C, \forall\, t \in T, \forall\, z \in Z$, where $\sum_{c\in C}\sum_{t\in T} k_{z,c}^t \ \le \sum_{c\in C}\sum_{t\in T}(\rho * \tau * w_{z,c}^t)\ \ \forall z \in Z$

We updated our Patient Capacity Requirements to be:

$$j^t * v^t * y_c^t \le \sum_{z\in Z} w_{z,c}^t \le v^t * y_c^t \qquad \forall\, c \in C, t = Technician$$

$$j^t * v^t * y_c^t \le \sum_{z\in Z}(k_{z,c}^t + w_{z,c}^t) \le v^t * y_c^t \quad \forall\, c \in C, \forall\, t \in Optemetrist/Ophthalmologist$$

The cost function can be updated to reflect screening and treatment costs, with α_c^t representing the cost for treatment appointments at clinic *c* with provider type *t*.

$$\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z}\left[(a_c^t + r * d_{z,c}) * w_{z,c}^t + (\alpha_c^t + r * d_{z,c}) * k_{z,c}^t + f_c^t * y_c^t\right] + h * \sum_{z\in Z}\left(n^u * p_z - \sum_{c\in C}\sum_{t\in T} w_{z,c}^t\right)$$

To set our objective functions, we first allocate a portion of our budget, b, to screening appointments. The proportion of the budget that should be allocated to screening is represented by gamma, γ, which is defined below. Note that the budget could be allocated in other ways.

$$\gamma = \frac{a_c^t}{(a_c^t + \alpha_c^t * \rho * \tau)}$$

We solve our updated model in two steps. First, we solve a screening-only model, similar to Model A in which we maximize the total number of people assigned to screening within the VHA. We keep our objective function as:

Maximize $\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z} w_{z,c}^t$

With updated budget constraint where budget is now $\gamma * b$ for screening:

$$\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z}\left[\left(a_c^t + r * d_{z,c}\right) * w_{z,c}^t + f_c^t * y_c^t\right] + h * \sum_{z\in Z}\left(n^u * p_z - \sum_{c\in C}\sum_{t\in T} w_{z,c}^t\right) \leq \gamma * b$$

The feasibility constraints for requirements on demand, provider capacity, and furthest traveling distance/time can remain the same.

We set a value, N, to our objective value from solving this model in our first step. In the second step, we solve the following objective function, seeking to maximize the number of people treated following screening plus the number of patients screened. In this objective function, the number of patients screened is multiplied by a negligibly small value, ν.

Maximize $\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z}(k_{z,c}^t + \nu * w_{z,c}^t)$

We use the cost function described above, subject to the total budget, b:

$$\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z}\left[\left(a_c^t + r * d_{z,c}\right) * w_{z,c}^t + (\alpha_c^t + r * d_{z,c}) * k_{z,c}^t + f_c^t * y_c^t\right] + h * \sum_{z\in Z}\left(n^u * p_z - \sum_{c\in C}\sum_{t\in T} w_{z,c}^t\right) \leq b$$

We additionally add the following constraint to ensure we are screening N patients:

$$\sum_{c\in C}\sum_{t\in T}\sum_{z\in Z} w_{z,c}^t \leq N$$

Solving this two-step optimization model allows us to maximize the number of patients who can be screened, while also maximizing the number of patients who can be treated following a positive screening result, subject to our model constraints.

2.3.1. Data

Patient data includes the number of individuals from each zip code in Georgia who used a Georgia VHA clinic location in 2017. Data about the VA system includes information about clinic locations, including street addresses, current number/types of providers at each location, salary and equipment costs for each provider type, and capacity for additional providers. Note that several clinic locations in Georgia did not offer eye care at any level at the time of this study.

We used GoogleMaps Application Programming Interface to calculate the driving distances and driving times from each patient zip code to each clinic location. The geographic centroid of each zip code was used to represent the origin for each of these distance/time determinations.

We followed Mission Act guidelines for the maximum driving distance (within 40 miles) and maximum driving time (within 60 minutes) for patients. (48) In our analyses, patients who live beyond these requirements are automatically assigned to community care outside the VHA system. Additional administrative data also came from the VA, including budgets and driving reimbursement amount.

When considering financial parameters, costs include direct costs of clinical operations, including equipment, facilities, and provider salaries. For TECS, we include both the costs of paying technicians to conduct in-person screening, as well as cost of optometrists or ophthalmologists to remotely review screening results. Each appointment scheduled within the

VHA incorporates screening material costs and patient driving reimbursement. Appointments scheduled outside of the VHA (with a community care provider) incur a fixed charge per visit.

2.3.2. Model Analyses

We conducted six major analyses, including: (1) examining how metrics are impacted when we move from current state to adding and/or redistributing providers within potential clinic locations; (2) considering a system without any providers currently at clinic locations; (3) varying the budget; (4) varying the number of patients required to be screened in the VHA; (5) including nearest-open-clinic constraints; and (6) including both screening and follow-up care requirements. These analyses and their results are outlined in Sections 2.3.2.1 – 2.3.2.6.

For each analysis, we consider the following metrics: number of patients assigned for chronic eye disease screening, average distance (in miles) that patients travel for screening, average time (in minutes) that patients travel for screening, cost for community care, cost for VHA care, and total system cost.

In all scenarios except our Current State (in the first analysis), inputs for each model specify that at least 10% of patients from each zip code must be screened in the VHA and at least 80% of each provider's capacity must be used. For Model A, a budget of $25 million is used, based on current VHA budgets. For Model B, at least 18,300 patients must be screened in the VHA, based on the Current State analysis in which we are maximizing the number of patients screened in the VHA.

2.3.2.1. Current State versus Additional Providers

In our first analysis, we maximize the number of patients screened in the VHA, subject to a budget, without moving the current providers or adding additional providers. In this first maximization problem, we *do not* require 10% of patients from each zip code to be seen because it would be infeasible, but this constraint is included in all other analyses. Next, we allow for providers to be added while keeping current providers at their respective locations and solve each model. Under Model A, we maximize patients seen given the same budget as current state. Under Model B, we minimize cost while requiring at least as many patients to be screened within the VA as are in current state.

For the Current State versus Additional Providers Analysis (Table 2), we see that in both Models A and B, we can screen more patients within the VHA than in current state when we consider additional providers, while remaining within budget. Additionally, the average distance and time traveled by patients is lower in both models compared to Current State. Critically, in both Models A and B (and all subsequent analyses), 10% of patients from each zip code are required to be screened in the VHA, which indicates Models A and B also improve geographical equity compared to current state. Note that 5,278 patients live beyond the VHA requirement for allowable driving distance and time (40 miles or 60 minutes) from any potential clinic location considered and are automatically assigned to community care in all analyses.

Table 2. Current State versus Considering Additional Providers

Metric	**Current State**	**Model A**	**Model B**
Number of Patients Screened in VA	18,300	75,000	29,640
Average Distance Traveled (miles)	22.7	12.6	12.8
Average Time Traveled (minutes)	31.6	21.0	20.3
Screening Cost - Internal	$6.1 M	$20.9 M	$9.0 M
Screening Cost – Community Care	$18.3M	$4.1 M	$15.5 M
Total Screening Cost	$24.4 M	$25.0 M	$24.5 M

2.3.2.2. No Current Providers Required

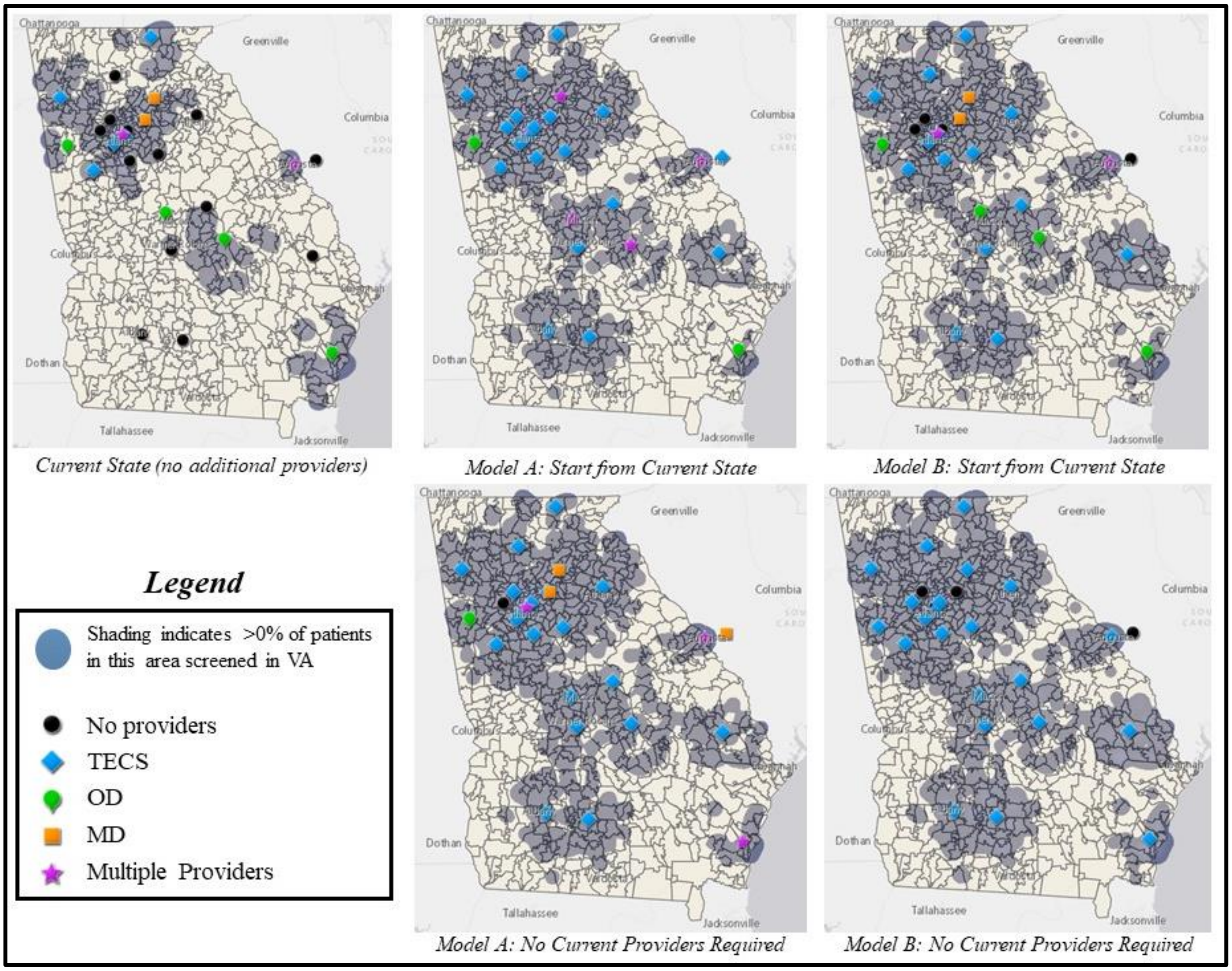
In our next analysis, we compare metrics for both models when we keep the clinic locations and patient counts/locations the same, but do not consider any of the current provider staffing levels (Table 3). Compared to when these providers are required to staff the locations where they currently work, our models show improved objectives: Model A yields over 7,000 more patients seen within the VHA for the same budget compared to when current providers are required; Model B demonstrates savings of over $1 million relative to current providers being required, while still seeing more patients than current state. These improvements are largely from including more technicians in locations currently staffed by ophthalmologists.

Table 3. No Current Providers Required

Metric	**Model A**	**Change from Model A with Current Providers**	**Model B**	**Change from Model B with Current Providers**
Number of Patients Screened in VA	82,278	+7,278	28,980	-660
Average Distance Traveled (miles)	14.7	+2.1	12.9	+ 0.1
Average Time Traveled (minutes)	23.3	+2.3	20.5	+ 0.2
Screening Cost - Internal	$22.7 M	+$1.8 M	$7.6 M	- $1.4 M
Screening Cost – Community Care	$2.2 M	-$1.9 M	$15.6 M	+ $0.1 M
Total Screening Cost	$24.9 M	- $0.1 M	$23.2 M	- $1.3 M

Figure 1 depicts maps that represent the results of our first two analyses. We see that by moving from the current state to adding more providers any model, the number of patients screened in the VHA across Georgia increases. Note that when we do not require any current state providers under Model B (minimize cost), we only staff technicians for screening.

Figure 1. Map Representation of Model Results



2.3.2.3. Impact of Budget

For the third analysis we consider only model A (maximize patients screened) and increase the budget by \$2.5 million and \$5 million to understand how budget impacts the maximum number of patients we can screen in the VHA. We next evaluate the impact of budget by increasing budget by \$2.5 million and \$5 million. These analyses were conducted only for Model A. The results (Table 4), indicate that varying the budget impacts several metrics, including number of patients screened in the VHA, average distance/time traveled, and per patient cost. As the budget increases, we are able to screen more patients. Interestingly, as the budget is increased, the average distance/time traveled increases as well. We review this relationship in our discussion.

Table 4. Impact of Budget (Model A) Analysis Results

Metric	Budget		
	$25 Million	**$27.5 Million**	**$30 Million**
Number of Patients Screened in VA	75,000	83,966	83,831
Average Distance Traveled (miles)	12.6	20.6	23.4
Average Time Traveled (minutes)	21.0	29.5	32.7
Screening Cost - Internal	$20.9 M	$25.6 M	$28.0 M
Screening Cost – Community Care	$4.1 M	$1.9 M	$1.9 M
Total Screening Cost	$25.0 M	$27.5 M	$30.0 M

2.3.2.4. Impact of Required Number Screened in the VHA

For the fourth analysis, we consider only model B (minimize cost) and increase the given number of patients required to be screened in the VHA to 30,000 and 40,000 patients to understand how this requirement impacts the overall cost to the system. The results of this analysis (Table 5) indicate that increasing the required number screened impacts the average distance/time traveled, and the per patient/system costs. The average distance/time traveled decreases as required number of patients screened increases, largely because the additional patients screened will be assigned from zip codes that are geographically near clinic locations. Assigning patients who live near clinics also allows the model to assign many more patients overall than the minimum number required to screen because if a provider is already at a location and has capacity to screen patients, it is cheaper to screen patients in the VHA instead of sending them to community care.

Table 5. Impact of Required Number Screened (Model B) Analysis Results

	Required Patients Screened in VA		
Metric	**18,300**	**30,000**	**40,000**
Number of Patients Screened in VA	29,640	30,900	40,980
Average Distance Traveled (miles)	12.8	12.0	10.2
Average Time Traveled (minutes)	20.3	19.5	17.7
Screening Cost - Internal	$9.0 M	$9.3 M	$11.9 M
Screening Cost – Community Care	$15.5 M	$15.2 M	$12.6 M
Total Screening Cost	$24.5 M	$24.5 M	$24.6 M

2.3.2.5. Requiring Patients to Visit the Nearest Open Clinic

In the fifth analysis, we consider model A, but add constraints that require patients to be screened at the clinic location that is both open and has the shortest distance from their home zip code. When constraints are added to require patients to visit the nearest open clinic, we see that fewer patients are screened within the VHA, compared to the baseline results of Model A (Table 6). Interestingly, the average travel distance and time both increase when these constraints are employed, largely because there are fewer providers assigned to staff clinics within the VHA system. Also, one may note that provider utilization is at 100% for all providers under Model A under baseline conditions; with the open nearest clinic constraints used, several providers are at less than 100% utilization.

Table 6. Impact of Nearest Open Clinic Constraints (Model A)

	Nearest Open Clinic Constraints	
Metric	**Without Constraints**	**With Constraints**
Number of Patients Screened in VA	75,000	66,806
Average Distance Traveled (miles)	12.6	13.2
Average Time Traveled (minutes)	21.0	21.5
Screening Cost - Internal	$20.9 M	$18.8 M
Screening Cost – Community Care	$4.1 M	$6.2 M
Total Screening Cost	$25.0 M	$25.0 M

2.3.2.6. Considering Screening and Follow-Up Care

In Model A+, we solve two consecutive MIPs, the first that maximizes the number of patients screened and the second which maximizes the number of patients who receive follow-up care. In the second MIP, we use the objective value of the first MIP as a lower-bound constraint on the number of patients who must be screened.

When we consider both screening and follow-up care in our model using Model A+, we see a decrease in the number of patients screened compared to Model A which considers screening only (Table 7). Note that Model A+ uses the same budget as Model A, so one can understandably assume that fewer patients will be screened because provider resources are now being used for follow-up care. Note that when we compare to baseline (maximizing patients screened with no additional providers), Model A+ still allows for screening an additional 9,000 patients while remaining within the $25 million budget, as well as providing follow-up care to over 2,000 patients.

Table 7. Impact of Incorporating Follow-Up Care

Metric	**Screening Only (Model A)**	**Screening + Follow-Up (Model A+)**
Number of Patients Screened in VA	75,000	27,461
Number of Patients Receiving Follow-up Care in VA	-	2,179
Average Distance Traveled (miles)	12.6	13.2
Average Time Traveled (minutes)	21.0	20.8
Care Costs - Internal	$20.9 M	$8.6 M
Care Costs – Community Care	$4.1 M	$16.0 M
Total Care Cost	$25.0 M	$24.7 M

2.3.2.7. Additional Note

Note that we also conducted analyses in which the allowable travel distance was varied. However, these analyses resulted in negligible variation in metrics. This lack of variation is largely due to the model rarely assigning patients to geographically distant clinics because driving reimbursement is considered in cost calculations and total costs are either constrained by a budget (Model A) or are being minimized as an objective (Model B).

2.4. Discussion

The results of the mixed-integer program for chronic eye disease screening in veterans can inform a broader understanding of how healthcare networks can be organized and how decision-makers may consider trade-offs. Additionally, we show how systems engineering tools can be used in both designing new healthcare networks and evaluating how modifications to existing healthcare networks impact key outcomes.

When making changes to an existing healthcare network, the systemic impact to patient access is not always intuitive. For example, when considering the impact to distance or time traveled in our chronic eye disease screening model, increasing the budget or increasing the required number of patients screened in the VHA yields a greater average travel distance/time. While one may think a substantial budget increase could decrease a metric like driving time, our example results in an increase because more patients from rural areas are being screened and still need to travel a considerable distance. However, if the VHA instead implemented more potential clinic locations (beyond the 28 locations considered in this example) for rural patients and/or considered using traveling technicians, the travel distance/time for patients may decrease when budget is increased. In such a scenario, shifting the budget to these alternative resources then may inhibit the number of providers who can be hired at urban locations, so fewer urban patients may be screened in the VHA. While a perfect solution may not exist, the tools discussed herein help decision-makers more fully understand how the design of their system impacts patient access.

Our models have some limitations. For example, we assign patients to specific providers; in reality, patients may prefer which provider(s) or location(s) they would like to visit. Additionally, while we attempt to include as many realistic constraints and parameters as possible in these engineering models, we typically cannot include all aspects of a scenario. Nevertheless, these tools can help guide decisions to understand where to consider future locations that may improve patient access while meeting several system requirements and patient constraints.

2.5. Generalizing Our Approach

In the chronic eye disease screening mixed-integer program described in previous sections, we sought to improve access to a healthcare service for veterans. We can use this specific model to consider a more generalized framework in which we seek to best align patients with providers and/or resources. Broadly, we can classify patients and providers into two or more levels and seek to align patients with providers who can best meet their needs.

Provider "levels" include two or more components of a healthcare providing organization that a patient may encounter. These components could be clinician providers, diagnostic or other tests, or medical equipment. Herein, we will focus on clinical providers, however, we will also discuss how other resources may be similarly considered in later paragraphs. We focus in particular on provider groups that offer similar types of frontline care but have different costs and skill sets.

For example, consider the eye care screening mixed-integer program model discussed in the previous sections. In this model, chronic eye disease screening was previously performed by either an ophthalmologist or an optometrist in a face-to-face visit. Each of these providers is licensed to provide eye disease screening, however both could provide services beyond screening, with an ophthalmologist providing even more services, like surgery, than an optometrist. We consider these providers as two levels of care available to a patient seeking an eye screening. Each provider level has an associated cost and supply, with the most specialized level (here, the ophthalmologist) tending to have the highest cost and lowest supply. Compared to the ophthalmologist, an optometrist would almost certainly be less expensive for frontline care, such as screening. If we move one step further, we can consider the TECS program described previously. The TECS program effectively adds a new provider level to the system's offering for chronic eye disease screening.

We can also divide patients into levels, with each level indicating the most appropriate "level" of services needed. Considering eye disease, we may have a group of patients who are unsure of their eye disease diagnoses and would benefit most from a screening, other patients with mild to moderate eye disease that can be monitored and cared for by an optometrist, and still other patients with severe eye disease requiring complex care from an ophthalmologist. Patients with less complex needs could use either providers who offer only frontline care or those providers who offer more in-depth care. In other words, a less-complex patient could see a highly-specialized or a less-specialized provider.

One can consider non-eye care settings for this hierarchical care framework. For example, colon cancer screening, which will be discussed in more detail in future chapters, has many levels of care and certain patients are best suited to receive care at one of those levels. (49)

For patients who have the highest risk for colon cancer, including disease history, a colonoscopy procedure provided by a gastroenterologist may be recommended. Alternatively, patients at low risk of colon cancer may be recommended to conduct an at-home fecal test, requiring fewer clinical resources and less patient burden. (50) Patients at moderate risk may still be recommended to receive a colonoscopy but not as frequently as those in the high-risk category. (51) In this brief description, we can see provider resource levels emerging (frequent colonoscopy, less-frequent colonoscopy, fecal testing), with patient risk levels aligning to each.

When considering how to implement a hierarchical healthcare network, we could attempt to match patients with providers at the same level. That is, more complex patients would be assigned to highly-specialized providers, moderately complex patients would be assigned to providers at a moderately-specialized level, and so on. Perfectly matching groups of patient demand and provider supply may be extremely challenging, however, due to initially unknown patient needs, and restrictions on the geographic locations where providers are willing to practice, as well as capacity and budget limitations. As we account for such real-world complexity in the system and patient population, we add these restrictions in our model. Constraints exist from the patient perspective, including patient preferences about providers, how far they are willing to travel, and their abilities to afford care. From the healthcare system perspective, one can consider where provider resources may be located, physical constraints on provider capacity, and how the system defines its patient catchment area.

As more of this complexity is considered, we consider trade-offs between different goals as we specify our key objective. For example, if we seek to minimize the system's cost, we may not be able to see as many patients or patients may have to travel a greater distance for their care. Conversely, if our goal is to see as many patients as possible, our costs will likely increase.

Systems engineering provides methods and tools that allow us to quantitatively consider such trade-offs.

Systems engineering tools are helpful for designing and evaluating provider networks. Key tools include linear programming, including integer and mixed-integer programming, and simulation models. (52–57) Systems engineers, in collaboration with administrative decision-makers, can use these tools to develop models that represent real-world scenarios. Such models can have meaningful results that inform operationally feasible decisions.

While lower cost alternatives do provide several benefits, decision-makers must ensure that patients' quality of care is maintained at an appropriate level compared to the care received with the highly specialized resource. If chronic disease screening is to be conducted by a less-specialized provider, screening options with this provider should still be of high quality and patients who use such providers should have equitable health outcomes to patients screened by highly-specialized providers.

Healthcare networks designed with hierarchical provider options help improve patients' access to frontline care, as shown in the TECS example. Prioritization may be set to improve access for particular patient subpopulations. For example, our case study enforces a minimum percentage of patients from all zip codes to be screened and restricts the maximum distance and time patients can drive to reach a clinic. This improves access for rural patients by requiring the network to have a geographically accessible location for most patients. Improved access to frontline care can improve patient outcomes by determining disease status, thus improving opportunities for patient education and treatment planning.

Hierarchical healthcare networks may be challenging to implement in practice. Ideal implementation opportunities include an existing healthcare system, like the VHA, with many geographically-dispersed care locations, distributing providers and other resources to improve access. Another example is an integrated health system attempting to expand ownership of clinical locations and considering new acquisitions. Both scenarios benefit from evaluating how to locate different types of providers to maximize patient access.

2.6. Conclusion

Systems engineering tools like mixed-integer programs can potentially improve patient access to care by establishing clinical locations geographically near patients and by distributing providers and other resources to appropriately meet patients' needs. Further, these tools can facilitate implementing such networks, both in designing networks and evaluating them to understand how patient access may be impacted when operational or policy changes are made. Partnerships between engineering professionals and clinicians, especially administrative decision makers, are critical to fully understanding the details of a specific system and how engineering tools can be employed.

The approach presented in this chapter can be extended to other applications. First, other specialties besides ophthalmology can be considered, especially those using frontline screening as a common entry point to care and those for which telehealth has already been shown to be an effective care modality, like dermatology. Additionally, these concepts could be applied to non-human resources such as medical equipment and testing. Finally, these models could be employed outside the VHA, although VHA's highly-integrated, cost-savings-incentivized organizational structure does lend itself particularly well to hierarchical networks.

Chapter 3. Simulating Appointment Scheduling Policies to Consider Clinical Need Versus Patient Preference for Telehealth

3.1. Introduction

Healthcare providers are increasingly using telehealth as an option for interacting with patients. (58) Telehealth can take many forms, including remote monitoring of intensive-care patients' clinical status and physicians conferencing via telephone to discuss complex patients. In some medical specialties, like gastroenterology, clinicians have begun to use synchronous video to meet with patients to replace or complement in-person appointments. (59) The use of such remote visits increased due to precautions related to the coronavirus pandemic that began impacting the United States in 2020, and continued use of telehealth is expected post-pandemic. (60) While some appointments may benefit from or necessitate meeting in-person, video visits may be effective alternatives for other appointments. Moreover, some patients may prefer a telehealth visit because an in-person visit may require them to travel a long distance, is more challenging to fit in their schedule, exposes them to risk of infection from other patients and healthcare providers, or other reasons.

Telehealth can improve access to care for patients. Geographic distance is a key barrier to care, especially for people living in rural areas and/or those who do not have access to reliable transportation. (1,61,62) When appropriately implemented, telehealth can reduce the distance patients need to travel in order to interact with the healthcare system. By decreasing travel, patients also save time otherwise spent on getting to and from appointments. This saved time may allow patients to better accommodate visits because they can take less time off of work or do not need to find childcare, which improves access to care from a logistical perspective. In a study of the impact of telehealth in inflammatory bowel disease (IBD), 80% of patients saved at least one half-day of driving by participating in a telemedicine visit. (63) Finally, telehealth has the potential to lower costs for a healthcare system, the savings from which can be passed on to patients. (13) These savings can mitigate patients' financial barriers to care. Telehealth lowers cost of care by using fewer physical resources and sometimes requiring fewer clinical/nonclinical staff members, including medical assistants, desk staff, and environmental services.

As telehealth has become more common, researchers have sought to understand patients' perceptions of telehealth. In a 2019 patient survey, 66% of patients reported being willing to use telehealth. Telehealth interest varies across age groups with older patients tending to be less interested in using it. (64) However, the same 2019 survey found that 52% of patients aged 65 or older are willing to use telehealth. Among older adults who have had a telehealth visit, more than half viewed in-person visits to have better overall quality of care compared to telehealth. (65) In gastroenterology, a study of the effectiveness of telehealth as an option for IBD visits found that 85% of patients reported their care was as good as it would have been in person. (63)

As clinical decision-makers incorporate telehealth options into their systems, simulation can be valuable for understanding how to effectively incorporate this modality. (54,66–68) Simulation is often used to guide healthcare decision-makers in evaluating alternatives, often by incorporating uncertainty. Discrete-event simulation is helpful in scenarios in which patients arrive and interact with a healthcare system via a set of clinical encounters. We add to this literature by applying simulation to a new context area that covers patient preferences for telehealth. Specifically, our model demonstrates scheduling policies that balance these patient preferences with clinical needs when scheduling appointments within the operational constraints of a clinic.

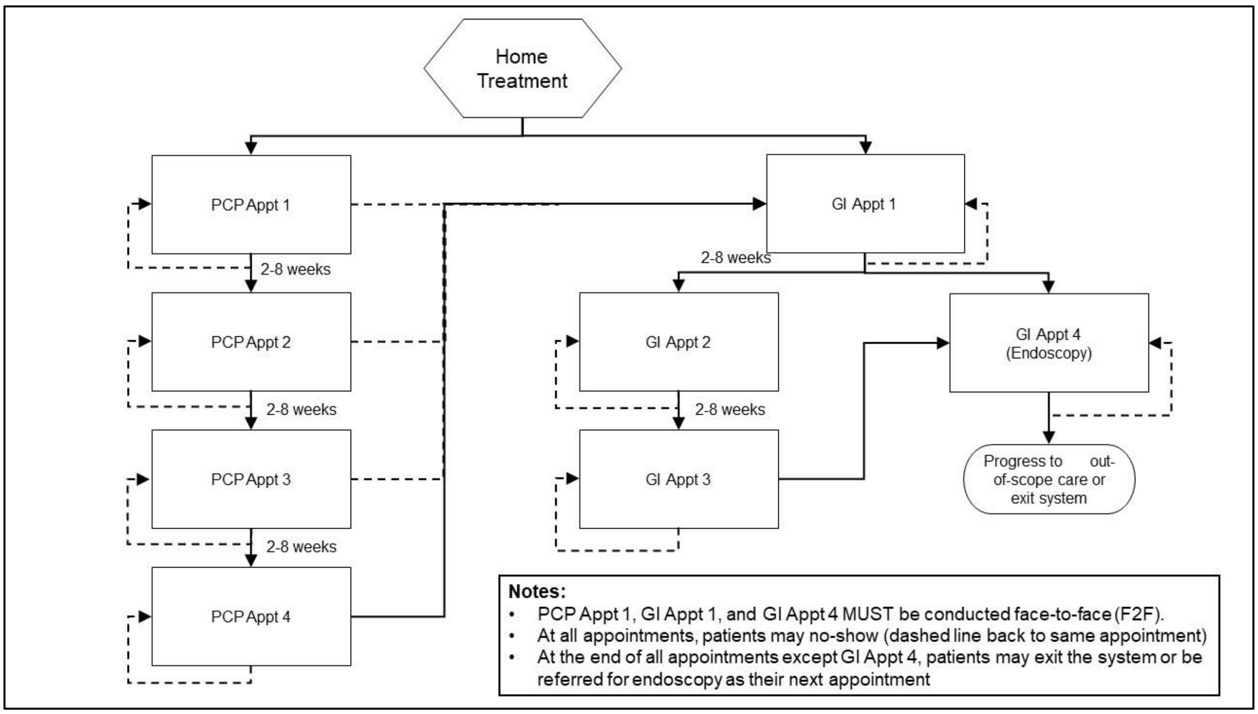
3.2. Problem Statement

As we demonstrate how simulation can be used to consider patient preference for telehealth, we focus on patients with gastroesophageal reflux disease (GERD) throughout this chapter. GERD is the most common gastrointestinal (GI) diagnosis in outpatient GI clinic visits in the U.S., with approximately 20% of adults reporting at least weekly GERD symptoms. (69) The clinical presentation of GERD primarily involves heartburn and acid regurgitation. GERD symptoms may also indicate more serious diagnoses like Barrett's esophagus and esophageal stricture. These diagnoses may be evaluated using additional testing such as upper endoscopy. Endoscopies occur if a provider determines a patient's symptoms require serious attention and/or if a patient visits a GI provider several times. GERD is an effective diagnosis to model for our problem context because it may involve care from multiple provider types (primary care and specialty care) and many GERD appointments can be conducted either in-person or via telehealth, as discussed further later in this section.

We evaluate GERD patients interacting with the Veterans Affairs (VA) Healthcare System gastroenterology clinic in Ann Arbor, Michigan. This care setting is ideal for conducting a simulation because, as an integrated healthcare delivery system, both VA primary care and GI providers belong to the same health system. Thus, patients can more easily be transferred between the two provider types.

GERD patients interact with the VA via several appointments as outlined in Figure 2. Patients tend to treat GERD symptoms at home with over-the-counter therapy prior to seeking clinical care. They then typically visit a primary care provider (PCP) or, less commonly, self-refer to a GI doctor. Regardless of provider type, a patient's first visit will be face-to-face (F2F) so providers can conduct physical examinations and in-person testing. After patients complete each visit they can either exit the system (either because their symptoms have been adequately treated or are lost to follow-up) or move to a future appointment. Most return visits have a specific time range for follow-up (generally 2-8 weeks). This range can be considered a clinically ideal range for their next appointment. We consider appointments scheduled within this range to be "in-range" and those outside of it to be "out-of-range."

Figure 2. Patient flow through GERD-related appointments



Patients visiting a PCP can be referred to a GI doctor after any appointment, and patients can be referred by their provider directly for an endoscopy if their symptoms indicate this would be clinically valuable. Patients may "no-show" for any appointment, in which case they are rescheduled for an appointment with the same provider and of the same type (F2F or telehealth). In our simulation logic, patients are dismissed from the system if they "no-show" three times over the duration of care. Aside from the first appointment with each provider type (PCP and GI) and the fourth GI appointment (endoscopy), the simulation assumes that all appointments can be conducted either F2F or via telehealth. Telehealth has been deemed to be an appropriate alternative to F2F visits for the appointments considered here, with no meaningful difference in quality of care.

3.3. Simulation Model

We modeled patients flowing through GERD-related clinical visits using discrete-event simulation. The simulation was coded and run in C++. The model is initiated with a set of providers, some of whom are primary care providers (PCPs) and some of whom are gastrointestinal (GI) specialists. Each provider has a given weekly capacity for number of face-to-face (F2F) and telehealth visits. In each replication, we randomly generate a stream of weekly patient arrivals that are Poisson distributed. Patients either seek care from a PCP or self-refer to a GI doctor. Each patient also has a preference for telehealth or face-to-face appointments and the probability of a patient preferring telehealth is based on the patient's geographic distance from the clinic. Patients who live "near" a clinic location (within 40 miles) have a 50% probability of preferring telehealth; 100% of those who live "far" from a clinic location prefer telehealth.

Patients flow through care for GERD and either do not attend a visit and are immediately rescheduled for the same visit (no-show) or do attend the visit. Patients who attend visits are scheduled for their next appointment based on a scheduling policy, as described in Section 3.3.2. The probability of which appointment is next needed is indicated in a transition probability matrix (example included in Appendix A). The transition probability matrix values are based on historical data from the Ann Arbor VA GI clinic.

Our base unit of time is weeks. The simulation is run over 52 weeks unless otherwise noted. To calculate minimum number of replications needed, we use appointment lead time as our metric of interest, with a standard error of 0.2 weeks, 95% confidence interval, and an initial replication size of 10. With baseline (BL) inputs and scheduling patients without regard for appointment modality preference, we find the minimum number of replications to be 39.8. (70) Our model processes in under one minute with 100 replications in most cases, so we increased to 100 replications for all analyses.

3.3.1. Model Input Parameters

We include several deterministic and stochastic input values for our model. Input values were derived from historical data, VA operations, and expert clinical opinions. A list of inputs is included in Table 8. Note that weekly provider capacities are specific to GERD patients. That is, we consider providers to only see 3 GERD patients via F2F appointments and 4 GERD patients via telehealth each week, but they may be seeing several other patients not included in this analysis.

Table 8. Simulation model inputs.

Parameter	***Baseline Value***	***Source/Description***
Number of PCPs	2	VA operations-Ann Arbor VA GI clinic
Number of GI doctors	2	VA operations-Ann Arbor VA GI clinic
F2F appointment weekly capacity per provider (PCP or GI)	3	VA operations-Ann Arbor VA GI clinic
Telehealth appointment weekly capacity per provider (PCP or GI)	4	VA operations-Ann Arbor VA GI clinic
Probability of next appointment type/probability of system exit	Varies based on current appointment	Historical data-Ann Arbor VA GI clinic
No-show rate (includes cancellations)	0.2	Historical data-Ann Arbor VA GI clinic

Average weekly new patient arrivals to PCP	5	Historical data (Poisson distribution with λ=5)
Average weekly new patient arrivals to GI providers	7	Historical data (Poisson distribution with λ=7) - Ann Arbor VA GI clinic
Proportion of patients who live far from clinic (defined by VA guidelines for "near" vs "far")	0.014	Historical data-Ann Arbor VA GI clinic, patients who live > 40 miles from clinic are considered "far," all others considered "near"
Probability of patient preference for telehealth vs. F2F visits	0.5 for "near" patients, 1.0 for "far" patients	(64,65)

3.3.2. Scheduling Policies

When a patient enters the system, they are scheduled for their first appointment with either a PCP or GI provider. Because all first appointments must be F2F, the simulation finds the first available F2F appointment with the appropriate provider and schedules the patient with a provider of that type. Once a patient has been scheduled with any type of provider, they are always seen by that provider for the appropriate appointments; that is, a patient is seen by at most one PCP and at most one GI provider.

After patients complete each visit, they are scheduled for a next appointment. When determining the patient's next appointment, we follow a policy which considers three parameters: patient's preference for appointment modality (telehealth vs. F2F), a range of time when the next appointment is clinically indicated ("in-range" vs. "out-of-range"), and provider available capacities. Unless otherwise noted, the ideal range of a next appointment is 2-8 weeks. Exceptions to this range include the patient's first appointment with any provider and an upper endoscopy (final GI visit), which are scheduled in the next open slot. Patients who no-show are immediately re-scheduled with the same provider for the next available appointment of the same type they should have attended. Patients see at most one PCP and one GI provider; that is, they are scheduled with the same provider for each visit offered within the set of PCP or GI appointments.

We construct a scheduling policy by combining an in-range policy (lettered A, B, C) and an out-of-range policy (numbered 1, 2) from Figure 3. For example, if we are following policy C2 and a patient who prefers telehealth needs a new appointment, we first attempt to schedule the soonest possible telehealth appointment within the next 2-8 weeks. If no telehealth appointments are available in this time frame, we then attempt to schedule the soonest possible F2F visit with the appropriate provider. If no appointments of any type are available in-range, we then schedule the patient for the soonest possible out-of-range appointment of their preferred type with the appropriate provider.

Figure 3. Scheduling policies used in the model

In-range Policies

A. First available appointment – any modality type (F2F vs. telehealth)
B. First available appointment – preferred modality type only
C. First appointment available of preferred modality type. If no in-range appointment of preferred modality type available, first available appointment of any type

Out-of-range Policies

1. First available appointment– any modality type
2. First available appointment – preferred modality type only

If no appointments are available out-of-range or if the patient's next appointment will be beyond the time horizon (e.g., it is week 52 of a 52-week analysis), we assume the patient is scheduled for an appointment beyond the horizon. These instances are tracked, but patients are not considered to have "completed" care.

3.3.3. Metrics

We track several metrics including lead time to first appointment, percentage of patients' appointment modality preferences met, provider utilization, number of patients who complete care, and number of out-of-range appointments. Lead time is calculated as the number of weeks between a patient "arriving" in the simulation to their first scheduled appointment. Percentage of modality preferences met considers the number of appointments could be scheduled for either F2F or telehealth (all appointments except the first visit with each provider and endoscopy) as the denominator and the number of those times in which a patient's preferred modality was scheduled as the numerator. Appointments that must be conducted F2F are not included in the denominator of total appointments when considering percent of modality preferences met. Provider utilization is the percentage of providers' available appointment capacities that are used for patient visits. The average number of out-of-range appointments is a count of the number of appointments that were scheduled outside of the clinically-ideal range, averaged across replications.

3.4. Analyses

We present several scenarios in considering patient preference for appointment modality when scheduling GERD patients. For these scenarios, we use scheduling policy C1 unless otherwise noted. Policy C1 indicates that when scheduling a patient in-range, we attempt to schedule the patient for the first available appointment of their preferred type. If no preferred appointments are available in-range, we attempt to schedule the patient for their non-preferred type in-range. If no appointments are available in-range, we schedule the patient for the first available appointment of any type out-of-range.

The four scenarios considered in this analysis include: (1) impact of a higher proportion of patients being far from clinic, (2) impact of patient arrival rates, (3) comparison of changing the number of providers versus changing provider capacity, and (4) comparison of scheduling policies. Additionally, we conduct sensitivity analyses to understand the inputs that have the greatest effect on key metrics. Table 9 lists output metrics when using the baseline inputs listed in Table 8 under policy C1.

Table 9. Baseline metric values, policy C1

Metric	***Value***	***Metric***	***Value***
Percent modality preference met	99.98%	Telehealth utilization	48.36%
Lead time	2.94 weeks	Overall provider utilization	70.12%
Patients seeking care	355.23	F2F utilization	99.13%
Patients completing care	299.01	Out-of-range appts.	119.06

3.4.1. Scenario 1: Distance to Care

In the first scenario, we vary the percentage of patients who live “far” (>40 miles) from the clinical location. In all analyses, 100% of patients who live far from care prefer telehealth appointments and 50% of patients who live near care prefer telehealth appointments. In our baseline analyses, 1.4% of patients live far from care, based on historical data of GERD patients at the Ann Arbor VA. Given that many other systems will have different proportions of patients who live far from care (or other demographics that influence likelihood of preferring certain appointment modalities), we vary the percentage of patients who live far from 0-50% to understand the impact on metrics.

Results from Scenario 1 are included in Table 10. We see that as more patients are far from care, overall (OA) provider utilization increases, largely due to increased telehealth appointment. As a greater proportion of patients are far from care, lead time decreases. This outcome is a result of more patients preferring, and thus being scheduled for, telehealth appointments according to policy C1. The relative increase of telehealth utilization frees more F2F appointments, which patients newly entering the system can use. Additional metrics that indicate clinical impact to patients like lead time and number of out-of-range appointments are not significantly impacted by changing the percentage of patients who live far from care.

In this scenario (also Scenarios 2 and 3), policy C1 accommodates patient preference appropriately, thus the percentage of modality preferences met is greater than 99% in all instances. This occurs because appointment capacity typically exists so patients get their preference for appointments that can be conducted in multiple modalities. Because of this, we do not report on percent preferences met for Scenarios 1-3.

Table 10. Impact of distance to care on utilization and lead time

	% of Patients who live far (>40 miles) from care					
Metric	***0%***	***1.4% (BL)***	***2.8%***	***10%***	***25%***	***50%***
OA Provider Utilization (%)	69.73 ±2.32	70.12 ±2.03	69.69 ±2.25	71.23 ±2.04	73.86 ±1.96	77.99 ±2.11
F2F Utilization (%)	99.02 ±0.71	99.13 ±0.71	99.08 ±0.81	98.94 ±0.90	98.77 ±0.93	98.01 ±1.45
Telehealth Utilization (%)	47.78 ±3.83	48.37 ±3.44	47.65 ±3.76	50.45 ±3.50	55.18 ±3.28	62.98 ±3.22
Lead Time (weeks)	2.98 ±0.32	2.94 ± 0.34	2.94 ±0.37	2.88 ±0.33	2.78 ±0.35	2.72 ± 0.32
Out-of-range appointments	117.68 ±18.73	119.06 ±17.14	118.16 ±20.04	117.35 ±17.36	115.27 ±19.65	121.32 ±19.44

3.4.2. Scenario 2: Patient Arrival Rates

In our baseline analyses, we model five patients arriving each week seeking care from a PCP and seven each week self-referring to a GI doctor, with each arrival rate being Poisson distributed. To understand how different patient arrival rates impact the system, we vary the PCP patients from 3-9 arrivals per week and the GI patients from 5-9 arrivals per week.

Table 11 shows the results from this scenario analysis. The general relationship between patient arrival rates and utilization is direct; as more patients arrive each week, utilization increases. The number of patients who self-refer to GI has a lesser impact on utilization than the number of patients who visit a PCP first. Lead time and patient arrival rates also have a direct relationship. However, when the PCP patient arrival rate decreases by 2 per week, the difference in lead time is statistically insignificant. All other changes to arrival rates presented here do indicate a significant difference in lead time. Similarly, the number of out-of-range appointments is impacted by arrival rate via a direct relationship. When arrival rates are either increased or decreased by 2 patients per week, the number of out-of-range appointments is significantly impacted. This relationship remains whether patients enter the system via PCP appointment or via self-referral, though changes in the arrival rates of self-referred patients has a larger impact on the number of out-of-range appointments compared to changes in arrival rates of patients arriving to a PCP appointment.

Table 11. Impact of patient arrival rates on utilization and lead time

	Weekly Patient Arrivals					
Metric	***5 PCP, 7 Self-Refer (BL)***	***3 PCP, 7 Self-Refer***	***7 PCP, 7 Self-Refer***	***9 PCP, 7 Self-Refer***	***5 PCP, 5 Self-Refer***	***5 PCP, 9 Self-Refer***
OA Provider Utilization (%)	70.12 ±2.03	61.91 ±2.75	72.05 ±2.05	72.43 ±1.92	68.77 ±2.17	70.13 ±2.03
F2F Utilization (%)	99.13 ±0.71	89.42 ±3.08	99.76 ±0.27	99.87 ±0.25	98.92 ±0.86	99.16 ±0.78
Telehealth Utilization (%)	48.37 ±3.44	41.27 ±3.67	51.27 ±3.60	51.86 ±3.34	46.15 ±3.69	48.35 ±3.54

Lead Time (weeks)	2.94 ±0.34	2.70 ±0.31	3.86 ±0.45	5.01 ±0.46	1.97 ±0.10	4.17 ±0.33
Out-of-range appointments	119.06 ±17.14	101.97 ±16.91	173.30 ±25.62	264.94 ±29.76	63.37 ±8.56	217.44 ±22.25

3.4.3. Scenario 3: Number of Providers vs. Provider Capacity

As health systems incorporate telehealth into care, they may consider how to adjust staffing. In this scenario we vary the number of providers. At baseline we have two PCPs and two GI doctors. We vary the number of each provider from 1-4. We consider how changing the number of providers compares to changing provider capacities. At baseline each provider has weekly capacity for four telehealth and three F2F GERD visits. We consider instances where both PCPs have a weekly capacity for two telehealth and one F2F visit ("lower capacity"), and where one of the two PCPs have a weekly capacity of seven telehealth and five F2F visits ("higher capacity"). We conduct the same set of capacity changes with GI doctors.

Tables 12 and 13 present analyses of the impact of provider count and capacity, respectively. Logically, as we decrease the number or capacity of providers, utilization and lead time increase; conversely, those metrics decrease when increasing provider count or capacity. When considering lead time, changing the number of providers in these scenarios has a greater impact than changing the capacity of providers. We see the largest impact when going from two to one PCP, with an increase in lead time of over 5 weeks.

Changing provider counts or capacity has a significant impact on the number of out-of-range appointments, with changes to PCP provider counts/capacity having a greater impact compared to GI. Of note, removing one PCP nearly triples the number of out-of-range appointments; removing one GI provider more than doubles this number. Because we are so often able to meet patients' preferences with Policy C1 and our current provider counts/capacities, increasing these values has a lesser impact on number of out-of-range appointments compared to decreasing counts or capacities.

Table 12. Impact of number of providers on utilization and lead time

	Provider Count				
Metric	***2 PCP, 2 GI (BL)***	***1 PCP, 2 GI***	***4 PCP, 2 GI***	***2 PCP, 1 GI***	***2 PCP, 4 GI***
OA Provider Utilization (%)	70.12 ± 2.03	75.01 ± 2.60	58.94 ±1.85	67.41 ±2.58	69.30 ±2.00
F2F Utilization (%)	99.13 ±0.71	99.93 ±0.18	82.46 ± 2.18	98.91 ±0.94	98.54 ±0.77
Telehealth Utilization (%)	48.37 ±3.44	53.65 ±4.83	37.23 ±2.56	43.79 ±4.40	45.38 ±3.45
Lead Time (weeks)	2.94 ± 0.34	8.63 ± 0.56	1.45 ±0.03	4.60 ±0.26	1.75 ±0.07
Out-of-range appointments	119.06 ±17.14	336.54 ±25.29	74.78 ±7.68	253.15 ±19.81	79.38 ±7.77

Table 13. Impact of provider capacity on utilization and lead time

	Provider Capacity				
Metric	***2 PCP, 2 GI (BL)***	***2 PCP (Low Cap.), 2 GI***	***2 PCP (High Cap.), 2 GI***	***2 PCP, 2 GI (Low Cap.)***	***2 PCP, 2 GI (High Cap)***
OA Provider Utilization (%)	70.12 ± 2.03	68.81 ± 2.15	64.59 ± 1.91	62.00 ± 2.53	70.25 ± 2.34
F2F Utilization (%)	99.13 ± 0.71	99.78 ± 0.39	95.79 ± 2.10	98.82 ± 1.02	99.04 ± 0.61
Telehealth Utilization (%)	48.37 ± 3.44	48.16 ± 3.61	41.61 ± 3.10	37.44 ± 4.01	43.79 ± 3.42
Lead Time (weeks)	2.94 ± 0.34	5.37 ± 0.50	2.64 ± 0.33	4.50 ± 0.23	2.00 ± 0.14
Out-of-range appointments	119.06 ±17.14	159.36 ±25.64	118.89 ±20.33	206.18 ±19.11	78.40 ±8.55

3.4.4. Scenario 4: Scheduling Policies

In the final scenario of our main analyses, we examine how different scheduling policies impact metrics. We consider the six combinations of in-range and out-of-range policies (A1, A2, B1, B2, C1, and C2). Table 14 indicates metrics for the various policies. We see policies A1 and A2 (“A policies”) tend to have different values than B1, B2, C1, and C2 (“B/C policies”). With the A policies, patient preferences for modality are met in approximately 50% of appointments, because A policies do not consider preference when scheduling. The B/C policies all have 99-100% preferences met. We also see higher overall utilization and telehealth utilization under the A policies versus the B/C policies. We also see a nonsignificant increase in lead time and number of out-of-range appointments in the A policies compared to B/C. These small increases are due to the slightly higher utilization of providers, especially for F2F appointments. Because any appointment can be used, providers are more likely to be unavailable, pushing appointments slightly further in time under A policies.

Table 14. Impact of scheduling policies on patient preferences met, utilization, and lead time

	Scheduling Policy					
Metric	***A1***	***A2***	***B1***	***B2***	***C1***	***C2***
% Appointment Preferences Met	50.09 ±3.37	50.68 ±3.27	99.97 ±0.09	100 ±0	99.98 ±0.06	100 ±0
OA Provider Utilization (%)	78.49 ±2.60	78.42 ±2.42	70.02 ±1.82	69.73 ±1.98	70.12 ±2.03	69.66 ±2.18
F2F Utilization (%)	99.49 ±0.57	99.50 ±0.46	99.13 ±0.66	99.08 ±0.63	99.13 ±0.71	98.94 ±0.97
Telehealth Utilization (%)	62.74 ±4.47	62.62 ±4.20	48.20 ±3.12	47.72 ±3.31	48.37 ±3.44	47.70 ±3.51
Lead Time (weeks)	3.07 ±0.34	3.06 ±0.30	2.96 ±0.34	2.95 ±0.36	2.94 ±0.34	2.93 ±0.33
Out-of-range appointments	127.76 ±19.31	127.95 ±17.83	121.10 ±22.05	116.61 ±16.92	119.06 ±17.14	116.84 ±17.76

4.5. Sensitivity Analyses

We conducted sensitivity analyses to understand which input variables have the greatest impact on two key metrics: lead time and provider utilization for telehealth appointments. For each metric a tornado diagram is created, with each bar of the tornado diagram representing one input variable. The top bar of the diagram indicates the input variable that has the greatest impact on the metric of interest, with subsequent bars included in descending order of impact. Appendix A has abbreviation explanations and full variable names.

Figure 4 shows tornado diagrams for lead time. In all policies, the most influential input variables are the number of PCPs, the number of GI physicians, and the lower-bound of the range of next appointment scheduling. Regarding number of physicians, we see that having fewer physicians, regardless of type, is highly influential on lead time, particularly when moving from two to one PCP.

Figure 4. Impact of input variables on lead time across all policies

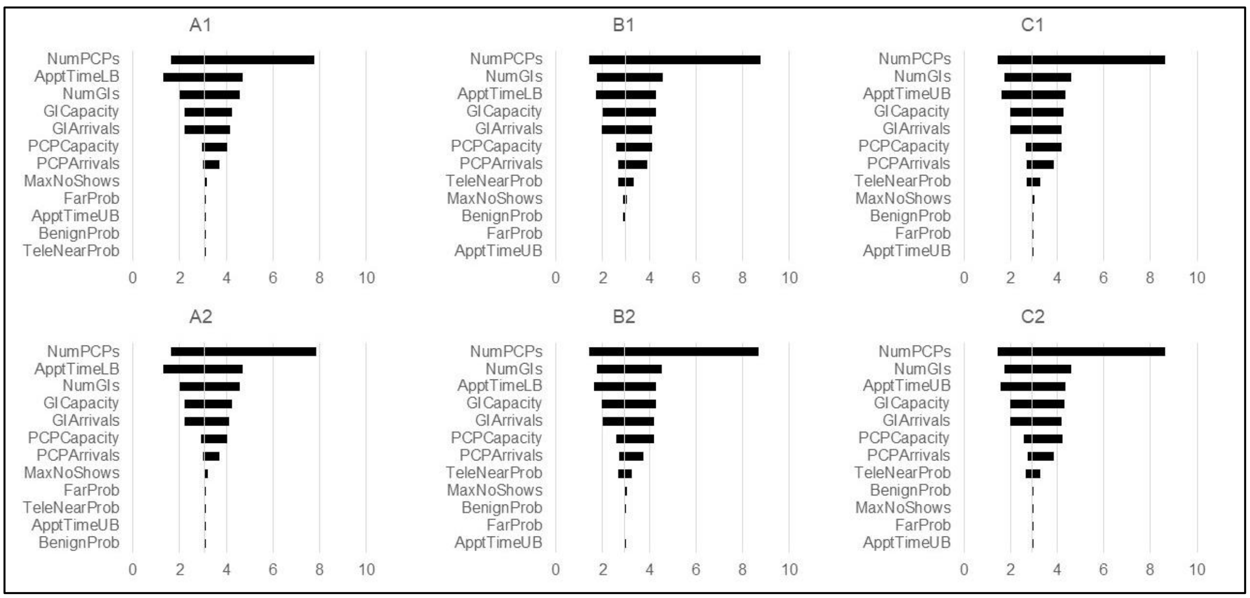
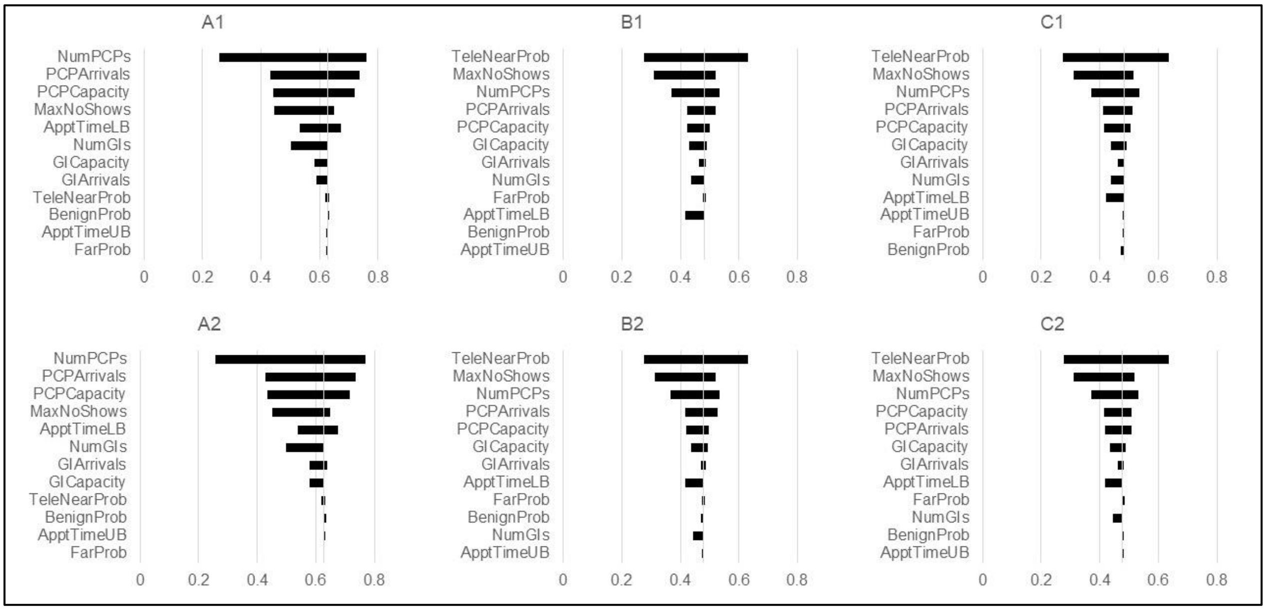


Figure 5 shows the influence of input variables on telehealth utilization across all policies. Telehealth utilization under policies A1 and A2 is most influenced by PCP-related input variables, including the number and capacity of PCPs. Telehealth utilization under B/C policies is most impacted by the probability of patients who live near clinics preferring telehealth appointments, which makes sense because these four policies all consider patient preference for appointment modality when scheduling.

Figure 5. Impact of input variables on telehealth utilization across all policies



3.5. Conclusion

In this chapter, we demonstrated how simulation can be used to understand how specialty care clinics can consider patient preference as they offer new ways of providing care to patients, including telehealth. As these modalities are implemented, simulation can be used to help define scheduling policies, such as the ones presented in our study of GERD patients. Further, simulation helps clinical decision-makers understand the impact of providing telehealth options for patients and providers. Simulation also helps these decision-makers adjust their systems to accommodate patient needs while maintaining operation objectives, such as achieving a given provider utilization or keeping patient lead times under a threshold.

Our simulation models demonstrate that, in our example, accommodating patient preference for appointment modality when scheduling specialty care appointments can be done with reasonable impact on the system and while incorporating patient preferences for care modality. Across the B/C policies, which take patient preference most into account, we see that patient preferences are met while achieving short lead times (less than 4-5 weeks in most scenarios) and appropriate provider utilization. These metrics are maintained under most instances of our sensitivity analyses. In particular, policy C1 indicates a balance between meeting patient needs (scheduling the patient for their preferred appointment modality when one is available in-range), while also offering scheduling flexibility for provider organizations if the patient's preferred appointment modality is not available in a clinically-indicated timeframe. Keeping lead time low will also maintain quality of care because the likelihood of a patient's condition worsening while waiting is smaller.

The discrete-event simulation presented here provides a helpful framework for how to organize models for other clinical institutions or diagnosis groups. Building on the model presented here, future work could include enhancing variable interactions, such as adjusting the probability that a patient is a "no-show" depending on whether their scheduled appointment is of their preferred modality. Additionally, we can extend this simulation to gain additional insight by incorporating financial information to understand impact on costs; imposing maximum lead-time policies; considering endogeneity on patient modality preferences due to scheduling policy changes; and incorporating additional patient attributes, such as age or socioeconomic status, that may impact patient preferences for telehealth.

Chapter 4. Evaluating Strategies for Mitigating Patient Backlog for Non-Emergency Outpatient Procedures Under Reduced Capacity Due to the COVID-19 Pandemic

4.1. Problem Background

On January 21, 2020, the Centers for Disease Control and Prevention confirmed the first case of the 2019 novel coronavirus, SARS-CoV-2, followed by the United States declaring the coronavirus outbreak a public health emergency on January 31. (71,72) On March 13, the United States federal government issued a national emergency due to the spread of SARS-CoV-2, while days prior the World Health Organization had declared a pandemic due to COVID-19, the disease caused by the coronavirus. (73,74)

Since that time, the COVID-19 pandemic has led to a remarkable number of hospitalizations and other demands on health systems across the country, including the cancellation or deferral of non-emergency medical appointments. (75) We can consider non-emergency appointments to be clinical visits that could be performed at a future date with little risk to a patient's condition worsening due to the delay. The length of time that non-emergency procedures can be delayed varies by the patient's condition and the severity of that condition.

During the COVID-19 pandemic, many non-emergency appointments were canceled or deferred to reduce the number of people in clinical settings, thus minimizing risk of coronavirus infection. (76) Additionally, during this time, health systems shifted many clinical providers and resources to caring for patients with COVID-19 and/or working to prevent coronavirus infection. Finally, state- and local-level government restrictions prohibited certain less urgent medical procedures from being performed. (77) These factors led to reduced capacity for many appointments, especially non-emergency outpatient visits. Outpatient visits are medical appointments that are conducted within a single day and do not require the patient to stay overnight at a medical facility.

4.1.1. Endoscopy

In this chapter, we use endoscopy as a demonstrative example of a non-emergency outpatient visit that experienced significant numbers of cancellations related to the COVID-19 pandemic. An endoscopy is a non-surgical gastroenterology (GI) procedure in which a clinician examines a patient's digestive tract using an endoscope, which is a flexible, thin tube with a camera at the end. (49) A common type of endoscopy is *colonoscopy*, in which the colon and rectum are examined for cancerous polyps and other indications of disease. Colonoscopy is considered the gold standard for screening and diagnosing patients for colorectal cancer and can also sometimes be used to treat polyps, bleeding, and other colorectal issues. (78)

Another common type of endoscopy is esophagogastroduodenoscopy, more commonly called *upper endoscopy*. During an upper endoscopy visit, a clinician examines a patient's upper GI tract, including the esophagus, stomach, and upper small intestine to evaluate issues including bleeding, inflammation, ulcers, and tumors. Similar to colonoscopy, upper endoscopy is often used for diagnosis, but can also sometimes be used to treat disease. (79) Note that additional types of endoscopy exist but we will only include colonoscopy and upper endoscopy in this analysis.

In either endoscopy visit, the patient is under sedation while being scoped, which usually lasts under one hour, with some time prior to scoping to prepare the patient and time after for recovery. The total time a patient spends in a clinic for an endoscopy visit is typically under four hours. (78,79)

Patients may seek an endoscopy visit for several reasons, with those reasons related to their urgency for the visit. The patient urgency categories discussed here are used in the Veterans Health Affairs (VHA) system, as well as in other health systems. The lowest urgency patients are those requesting a colonoscopy for *screening*. These patients have no underlying risk factors for colorectal cancer aside from age of at least 50 years. *Surveillance* patients are seeking colonoscopy because they have additional risk factors for disease, often previous malignancies. Surveillance patients can be split into two categories, *low-risk* and *high-risk*, depending on the number and severity of their risk factors, including the size of adenomas previously removed. Finally, *diagnostic* patients are those seeking endoscopy because some previous screening test has indicated a high likelihood of disease. In our model, all patients seeking upper endoscopy are classified as diagnostic patients, and patients may seek colonoscopy for diagnostic reasons as well. The distribution of patient urgency categories in the Ann Arbor VHA is listed in Table 15.

Table 15. Distribution of endoscopy patients by risk category

Risk Category	***Average Weekly Arrival Proportion***
Screening Colonoscopy	23%
Low-Risk Surveillance Colonoscopy	15%
High-Risk Surveillance Colonoscopy	15%
Diagnostic – Colonoscopy	25%
Diagnostic – Upper Endoscopy	22%

4.1.2. FIT: Fecal Immunochemical Tests

Rather than coming to a clinical facility for a colonoscopy, *screening* patients can alternatively use a fecal immunochemical test (FIT), in which the patient's stool is examined for blood. FIT has been demonstrated to be a clinically effective alternative to colonoscopy for screening patients for colorectal cancer, though to maintain effectiveness, patients need to participate in FIT more frequently than they would colonoscopy (once per year for FIT compared to approximately once every five-seven years for colonoscopy). (50)

If a patient uses FIT, the clinic provides the supplies needed to collect the sample and the patient returns the sample to the clinic, either by traveling to the clinic to return or by returning via mail. (80) While FIT still requires resources from the clinical facility and often still requires the patient some travel, FIT notably does not require an in-person appointment with a clinician. This feature is especially helpful during the COVID-19 pandemic, when colonoscopy appointment capacity is reduced.

If a patient's FIT result is positive, they are recommended to receive a colonoscopy. In this case, their urgency increases and the VHA considers them now to be *diagnostic* patients when they are being scheduled for colonoscopy. Patients who receive negative FIT results do not require any further care, but are recommended to continue following screening guidelines, including participating in future FIT or screening colonoscopy.

4.1.3. Capacity Reduction and Backlog Mitigation Strategies

Like many clinical facilities across the country, VHA clinics saw reduced capacity for endoscopy during the COVID-19 pandemic, with over 7 million appointments canceled between March 15 and May 1, 2020. (76) While there is some evidence to indicate that patients were more likely to delay non-urgent medical care, thus decreasing demand for appointments like endoscopy, the patients' clinical needs related to endoscopy are no different because of COVID-19. (81) We can therefore assume that approximately the same number of patients should be receiving endoscopy or some alternative form of GI care (FIT, etc.), despite the reduction in available capacity. Further, we can then assume that while endoscopy appointment capacity was reduced, the number of patients waiting for an endoscopy visit was increasing.

Early in the widespread onset of the COVID-19 pandemic, the capacity for non-emergency outpatient visits like endoscopy was reduced significantly; in our model, we assume a reduction to 5% of standard capacity for the first 10 weeks. (81) As healthcare leaders learned more about COVID-19, they determined solutions to keeping patients and providers safe in clinical environments. These solutions, as well as mitigation of community-spread COVID-19, allowed for more appointment capacity to be gradually readded. Nevertheless, the backlog of patients waiting for endoscopy may persist unless the VHA changes how it provides endoscopy visits and related care.

The VHA has identified several strategies to mitigate the potential backlog of patients while capacity is reduced. Several strategies triage patients based on urgency of their need for an endoscopy and redirect their care. We can also consider operational strategies, including adding additional days in which endoscopy is offered to patients. Note that the strategies discussed herein do not need to be administered in isolation and our analysis considers their potential individual impacts, as well as how they may mitigate backlog when used in combination.

4.1.3.1. Exchange Strategy

In the first strategy, *Exchange*, patients who are requesting an endoscopy for *screening* are redirected to at-home FIT instead of coming into clinic for endoscopy. Because screening patients account for approximately 30% of endoscopy visits, this strategy helps greatly reduce the number of patients waiting for an endoscopy visit.

In the Exchange strategy, all screening patients are recommended to FIT, but some percentage of patients “decide” to not use FIT. The patients who “decide” to not use FIT exit the system. Of those who do use FIT, some percentage receives a positive result. Those patients who receive a positive FIT result, rejoin the queue as *diagnostic* patients. Those who receive a negative result exit the system.

4.1.3.2. Extend Strategy

In the *Extend* strategy, *low-risk surveillance* patients who are seeking endoscopy are deferred for two years. This strategy is in relation to updated guidelines from the American Society for Gastrointestinal Endoscopy, which indicate that that low-risk surveillance patients need to receive endoscopy every 7-10 years to monitor potential disease progression. (82) The VHA previously followed a guideline which recommended an interval of 5-10 years between endoscopy visits for these patients. (51) At the onset of the COVID-19 pandemic, the low-risk surveillance patients seeking endoscopy were being scheduled according to a five-year interval. If the Extend strategy is in place, the VHA now shifts these patients to a seven-year interval between endoscopy, thus low-risk surveillance patients are deferred for two years before seeking an endoscopy.

4.1.3.3. Overtime Strategy

An operational strategy for mitigating backlog of patients waiting for endoscopy is the *Overtime* strategy. When the VHA uses the Overtime strategy, additional days or portions of days are available for patients to be scheduled for endoscopy. We can assume that endoscopy clinics typically operate Monday through Friday, a five-day week. Thus, if the clinic decides to add Saturday as an available day for endoscopy visits, the weekly capacity increases by 20%. Alternatively, if the clinic is only open for a half-day on Saturday, the weekly capacity would increase by 10%.

In the Overtime strategy, we increase the weekly capacity by 10-40% (one half-day to two full days of weekend clinic visits). Note that weekly capacity is increased by a percentage of what would be currently offered in a given week under administrative capacity reduction. For example, if a clinic typically offers 100 endoscopy visits each week, they may only offer five visits each week during the early weeks of the COVID-19 pandemic, a reduction to 5% of their original capacity. If the overtime strategy is in place at 20% overtime, the 20% increase in capacity is applied to the five visits, so the clinic would offer six endoscopy visits per week.

4.2. Methods

We developed a discrete-event simulation model to consider the various strategies for assigning patients to endoscopy appointments under reduced capacity. We compare the three strategies outlined in the previous section, as well as combinations of those strategies, to each other. We also compare these strategies to implementing no strategies (*No Triage*).

In the model, patients “arrive” each week to seek endoscopy, with the number of patients arriving randomly determined via a Poisson distribution with mean 113 patients. Patients are randomly assigned an urgency categorization (screening, low-risk surveillance, etc.) based on the distribution indicated in Table 15. In each week, we first assign patients with the highest urgency to endoscopy visits. Diagnostic patients, which include both diagnostic colonoscopy and upper endoscopy, are assigned first, then high-risk surveillance, and so on. Within each patient category, those who have been waiting longest are prioritized for assignment. Patients not assigned within a given week join a queue.

Note that we initialize our model with 802 patients already in the system. These patients represent those who had appointments at the time of capacity reduction. Within the simulation logic these patients must be seen prior to any patients who have “arrived” after the simulation starts. These initial patients are not included in any metric calculations.

Our typical (pre-pandemic) capacity is 110 endoscopy appointments. In our analyses, we begin with capacity for endoscopy visits reduced to 5% of typical capacity. After 10 weeks, capacity is increased to 50%, and then increased to 100% capacity after 10 more weeks. This leads to 14,630 total appointment slots over the course of the simulation, which indicates the maximum number of patients we can see without increasing capacity using the Overtime strategy.

Additional baseline inputs are listed in Table 16. The base unit of time in our model is weeks. We run the simulation for 150 weeks and replicate 100 times. With baseline inputs, we find the minimum number of replications to be 57 when comparing No Triage to the Exchange strategy. (70) Our model typically processes in under five minutes with 100 replications in most cases, so we increased to 100 replications for all analyses. Our simulation was coded in C++.

We report metrics such as number of patients seen, average wait time, and average number of patients waiting beyond four weeks for a visit. This final metric is important to VHA clinics because patients who wait beyond four weeks are eligible to have their appointment costs covered if they seek care from non-VHA providers. In our baseline analyses, we only track these patients who wait beyond four weeks, but we also explore scenarios in which those patients leave the system with some probability greater than zero.

Table 16. Baseline Input Parameters

Parameter	***Value***	***Notes***
Weekly New Patient Arrivals	113	Poisson distributed with lambda=113. Source: Ann Arbor VHA (Note: See Table 1 for distribution of patients by urgency)
Weekly Endoscopy Capacity	110	Source: Ann Arbor VHA
Likelihood that Screening Patients follow-through with FIT	85%	Source: Ann Arbor VHA
Likelihood of Positive FIT	15%	Source: (83)
Weeks between FIT recommendation and result	4	Source: Ann Arbor VHA
Patients in system at simulation start	802	Source: Ann Arbor VHA (Note: metric calculations do not include these patients)
Capacity		
Weeks 1-10	5%	Source: Ann Arbor VHA
Weeks 11-20	50%	Source: Ann Arbor VHA
Weeks 21-30	75%	Source: Ann Arbor VHA
Weeks 31-150	100%	Source: Ann Arbor VHA

4.3. Results

4.3.1. Baseline Analyses

In our baseline analyses, we compare our three strategies for mitigating patient backlog – Exchange, Extend, and Overtime – to each other and to implementing no strategies (No Triage) as shown in Table 17. Under No Triage, we see 14,289 patients over 150 weeks, however only 964 screening patients are seen of approximately 3,900 screening patients who are seeking appointments. Further, over 5,000 patients are waiting beyond four weeks and the average wait time is 22.8 weeks across all patient categories, with screening patients waiting an average of 70.3 weeks.

Table 17. Baseline Analysis Results

Metric	***No Triage***	***Exchange***	***Extend***	***Overtime***
Number of Patients Seen	**14,289**	**13,812**	**14,287**	**17,198**
Screening	964	0	2,724	3,856

Low-Risk Surveillance	2,513	2,513	766	2,519
High-Risk Surveillance	2,509	2,507	2,512	2,517
Diagnostic	8,303	8,792	8,285	8,306
Num. Patients Waiting >4 Weeks	**5,445**	**2,816**	**3,448**	**3,732**
Screening	2,960	0	1,854	1,640
Low-Risk Surveillance	971	1,165	0	787
High-Risk Surveillance	655	742	685	581
Diagnostic	869	909	909	724
Average Wait Time (weeks)	**22.8**	**9.8**	**14.1**	**11.3**
Screening	70.3	-	41.3	33.2
Low-Risk Surveillance	23.1	28.8	0.0	10.1
High-Risk Surveillance	9.4	10.9	9.4	5.7
Diagnostic	3.9	4.0	3.8	3.0

When the Exchange strategy is implemented, we see fewer patients for visits, with all screening patients being recommended for FIT instead of coming to the clinic for a colonoscopy visit. If those patients have a positive FIT, they return to the system as diagnostic patients. With the Exchange strategy in place, the number of patients waiting beyond four weeks is approximately halved and the average wait time decreases to 9.8 weeks. Note that with this strategy in place, the average waiting times for low-risk and high-risk surveillance patients increase. This increase is due to the screening patients who have a positive FIT result and return for endoscopy as diagnostic patients who are now prioritized ahead of either surveillance group.

With the Extend strategy, we see approximately the same number of patients overall as compared to No Triage, however we see more screening patients and fewer low-risk surveillance patients. Both the number of patients waiting beyond four weeks and the average wait time decrease to 3,448 and 14.1 weeks, respectively. Notably, the average wait time for screening patients still remains extremely high at 41.3 weeks. When the Extend strategy is implemented, one should note that several low-risk surveillance patients who have been intentionally deferred their endoscopy visit will need an endoscopy visit after the simulation end date. In this case, because low-risk surveillance patients are deferred for two years, there will be approximately 1,750 low-risk surveillance patients who will need endoscopy visits over the course of the two years following simulation end. During the final 46 weeks of the simulation, we will begin seeing the low-risk surveillance patients who were deferred during the early weeks of the simulation who have now returned for endoscopy following their two-year deferral.

When incorporating Exchange and/or Extend, we will always see a reduction in the number of patients seen because screening and/or low-risk surveillance patients are triaged to an alternative to immediate endoscopy. While the VHA seeks to provide the best patient care to all eligible patients whenever available, immediately providing an endoscopy visit for all patients is not necessarily the ultimate goal, especially when clinically-proven alternatives like those used in the Exchange and Extend strategies are available.

With the Overtime strategy, we see the most patients of any strategy in our baseline analysis, with all patients who arrive in the simulation being seen before the simulation ends. If the goal of these strategies is to ensure all patients are seen, the Overtime strategy achieves that goal. However, because this strategy just increases capacity without triaging lower-urgency patients, we see more patients waiting beyond four weeks compared to the Exchange and Extend strategies (though still markedly lower than the No Triage strategy) and an average patient wait time of 11.3 weeks, which is greater than the Exchange strategy.

4.3.2. Combining Strategies

The Exchange, Extend, and Overtime strategies are not mutually exclusive so we can examine how combining strategies impacts our metrics (Table 18). We examine pairs of each strategy, as well as all three strategies included at once.

Table 18. Combining Strategies

Metric	*Exchange + Extend*	*Exchange + Overtime*	*Extend + Overtime*	*All Strategies*
Number of Patients Seen	**12,072**	**13,804**	**15,541**	**12,074**
Screening	0	0	3,973	0
Low-Risk Surveillance	767	2,502	766	771
High-Risk Surveillance	2,509	2,514	2,513	2,512
Diagnostic	8,796	8,788	8,289	8,791
Num. Patients Waiting >4 Weeks	**1,566**	**2,110**	**2,617**	**1,274**
Screening	0	0	1,203	0
Low-Risk Surveillance	0	771	0	0
High-Risk Surveillance	651	539	590	514
Diagnostic	915	800	824	760
Average Wait Time (weeks)	**5.2**	**5.2**	**5.8**	**3.6**
Screening	-	-	12.7	-
Low-Risk Surveillance	0.0	11.3	0.0	0.0
High-Risk Surveillance	10.9	6.3	5.7	6.3
Diagnostic	4.0	3.1	3.0	3.1

With Exchange and Extend strategies in place, we see far fewer patients because all screening patients are recommended to FIT and all low-risk surveillance patients are deferred for two years. Fewer patients wait beyond four weeks and the average wait time is nearly halved compared to using the Exchange strategy alone (5.2 weeks with both strategies compared to 9.8 with Exchange alone).

With Exchange and Overtime, we see an increase in number of patients seen compared to the previous combination of strategies, but more patients are waiting beyond four weeks. The Exchange/Overtime combination has the same average wait time as Exchange/Extend (5.2

weeks) but the average wait time for diagnostic and high-risk surveillance is shorter with Exchange/Overtime, while low-risk surveillance patients are waiting longer.

Among the combined-strategy scenarios, the most patients are seen (15,541) when both Extend and Overtime strategies are used, but we also see the largest number of patients waiting beyond four weeks (2,617) and the greatest average patient wait time (5.8 weeks).

When all strategies are used, a similar number of patients are seen to just Exchange and Extend, indicating that we do not need the additional capacity provided by the Overtime strategy in order to see all patients with Exchange and Extend in place. That additional capacity does allow patients to have visits sooner. This leads to decreases in the number of patients waiting beyond four weeks and the average patient wait time. Yet, when all three strategies are used, we will have a great deal of unused capacity after the initial backlog of patients receives visits.

4.3.3. Varying Triage Uptake

Triage strategies may not be able to be fully implemented due to patients and/or providers being unwilling to adhere to triage guidelines or inadequate resources (not enough FIT kits, etc.). Tables 19 and 20 present results when the Exchange or Extend strategies are not fully implemented. The first column of results in each table shows 100% implementation, which will have the same results as the respective strategy in Table 17, followed by 75%, 50%, and 25% implementation. When a strategy is partially implemented the remaining patients who would have used that strategy are processed as though there is no strategy in place.

Table 19 shows the impact of varying the Exchange strategy. When less than 100% of screening patients are triaged to FIT, more patients are seen overall. However, we do not see an increase in overall patients seen beyond 75% implementation. This is largely due to some screening patients who *do* participate in FIT returning to the system because of a positive FIT result as diagnostic patients, who are prioritized ahead of screening patients who do not participate in FIT. Additionally, as the proportion of screening patients decreases, the number of patients waiting beyond 4 weeks increases, as does the average waiting time.

Table 19. Varying Exchange Implementation[1]

Metric	***100% Exchange***	***75% Exchange***	***50% Exchange***	***25% Exchange***
Number of Patients Seen	**13,812**	**14,293**	**14,290**	**14,290**
Screening	0	600	723	813
Num. Patients Waiting >4 Weeks	**2,816**	**3,447**	**4,230**	**4,833**
Screening	0	760	1,476	2,252
Average Wait Time	**9.8**	**13.1**	**16.6**	**19.9**
Screening	-	66.2	68.9	70.2

Table 20 presents results when the Extend strategy is varied. Unlike the Exchange strategy variations, the Extend strategy impacts two patient groups: Screening and Low-Risk Surveillance. Because of the prioritization structure of our model, low-risk surveillance patients are always prioritized ahead of screening patients. Thus, if fewer low-risk surveillance patients are deferred for endoscopy, more of these patients in this group will consume capacity soon after their arrival, which will leave fewer visits available to screening patients. As Table 20 demonstrates, lowering the proportion of patients who follow the Extend strategy has no impact on the total number of patients seen, but does lead to large increases in the number of patients waiting beyond four weeks and average wait time.

[1] In Tables 19 and 20, all patient categories are included in the simulation as in previous analyses, but these tables only report patient categories with metric values that significantly change across scenarios.

Table 20. Varying Extend Implementation[1]

Metric	***100% Extend***	***75% Extend***	***50% Extend***	***25% Extend***
Number of Patients Seen	**14,287**	**14,294**	**14,292**	**14,291**
Screening	2,724	2,361	1,878	1,501
Low-Risk Surveillance	766	1,134	1,597	1,996
Num. Patients Waiting >4 Weeks	**3,448**	**3,795**	**4,246**	**4,708**
Screening	1,854	2,057	2,212	2,436
Low-Risk Surveillance	0	215	459	726
Average Wait Time	**14.1**	**16.2**	**18.5**	**20.3**
Screening	41.3	48.9	57.5	63.5
Low-Risk Surveillance	0.0	7.4	12.9	17.2

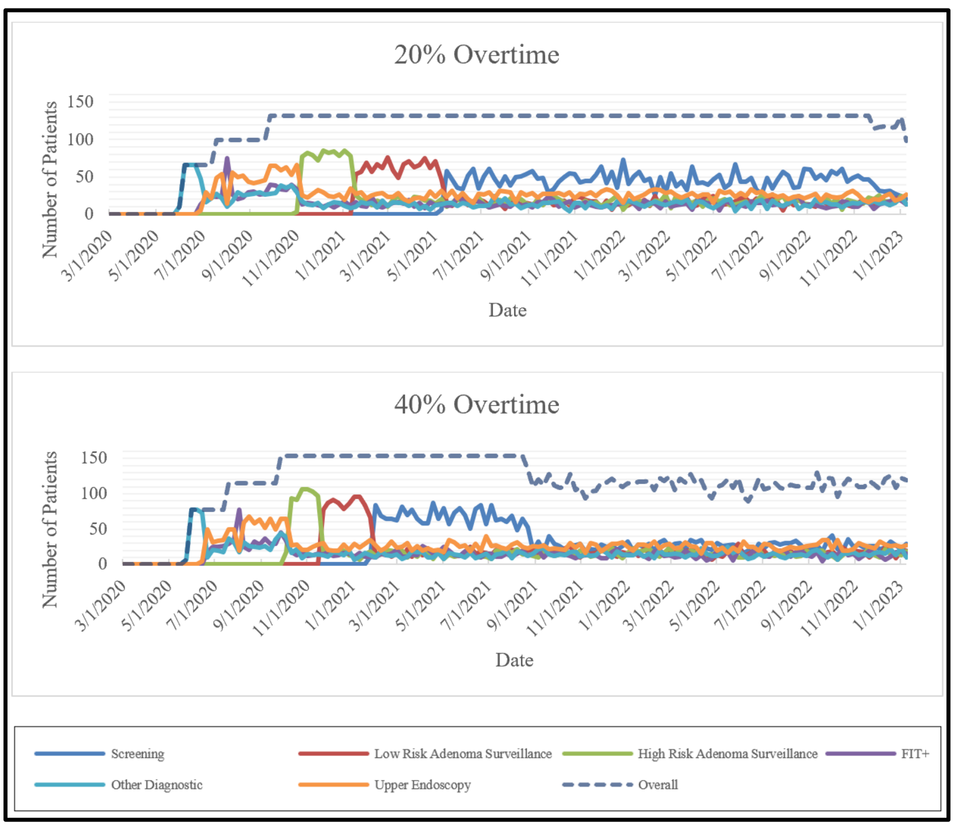
4.3.4. Varying Overtime

In our earlier analyses, the Overtime strategy considered an increase in capacity of 20%, the equivalent of keeping clinics open one full weekend day. We can also consider 10% overtime (one weekend half-day) or 40% overtime (two weekend full days), with results shown in Table 21. With 10% overtime, fewer patients are seen overall compared to 20%, with more patients waiting beyond four weeks and a greater average patient wait time. When overtime is increased to 40%, we do not see a significant increase in number of patients seen, but there is a meaningful decrease in the number of patients waiting beyond four weeks and average patient wait time. With 40% overtime, there will surely be unused capacity throughout much of the simulation period, as shown in Figure 6, which indicates number of patients seen by week. Under the 20% Overtime strategy, we use all available capacity for nearly all of the simulation period. Conversely, under the 40% Overtime strategy, we have available capacity through most of the latter half of the period.

Table 21. Varying Overtime Implementation

Metric	*10% Overtime*	*20% Overtime*	*40% Overtime*
Number of Patients Seen	**15,748**	**17,198**	**17,290**
Screening	2,446	3,856	3,964
Low-Risk Surveillance	2,505	2,519	2,502
High-Risk Surveillance	2,499	2,517	2,510
Diagnostic	8,298	8,306	8,314
Num. Patients Waiting >4 Weeks	**4,443**	**3,732**	**2,870**
Screening	2,106	1,640	1,152
Low-Risk Surveillance	868	787	560
High-Risk Surveillance	617	581	463
Diagnostic	852	724	695
Average Wait Time	**17.0**	**11.3**	**5.7**
Screening	53.5	33.2	13.0
Low-Risk Surveillance	14.2	10.1	6.3
High-Risk Surveillance	7.2	5.7	4.3
Diagnostic	3.4	3.0	2.5

Figure 6. Number of Patients Seen by Week Under Two Overtime Strategies



4.3.5. Sensitivity Analyses of Assumed Inputs

While no simulation model can fully capture reality, we can conduct sensitivity analyses to ensure we are capturing more potential realistic scenarios. Table 22 presents examples of such scenarios. In all scenarios, we assume the Exchange and Extend strategies are both used, with the first column of results presenting the same output as was shown in the original combined strategy table (Table 18). In the next two columns, we show results that change the average number of weekly arrivals, first by increasing by 25%, then by decreasing by 25%. The decreased arrival rate is particularly helpful because patients may have been less likely to seek non-emergency care during the COVID-19 pandemic. The results in these columns indicate a direct relationship between arrival rate and all of our metrics. That is, increasing the arrival rate leads to an increase in number of patients seen, number of patients waiting beyond four weeks, and average wait time. Decreasing arrival rate leads to decreases in these metrics.

Table 22. Varying Additional Assumptions

Metric	***Baseline (Exchange + Extend)***	***Arrivals +25%***	***Arrivals -25%***	***0.5 Prob. Patient Leaves if Wait >4 wks***	***1.0 Prob. Patient Leaves if Wait >4 wks***
Number of Patients Seen	**12,072**	**14,211**	**9,090**	**10,683**	**10,646**
Screening	0	0	0	0	0
Low-Risk Surveillance	767	130	577	771	771
High-Risk Surveillance	2,509	3,126	1,878	2,143	2,168
Diagnostic	8,796	10,955	6,635	7,769	7,707
Num. Patients Waiting >4 Weeks	**1,566**	**3,703**	**992**	**213**	**0**
Screening	0	0	0	0	0
Low-Risk Surveillance	0	844	0	0	0
High-Risk Surveillance	651	1,391	393	53	0
Diagnostic	915	1,468	599	160	0
Average Wait Time	**5.2**	**12.5**	**3.1**	**0.2**	**0.1**
Screening	-	-	-	-	-
Low-Risk Surveillance	0.0	22.8	0.0	0.0	0.0

High-Risk Surveillance	10.9	32.4	5.0	0.2	0.1
Diagnostic	4.0	5.9	2.8	0.2	0.1

We can also consider patients leaving the system if they wait beyond four weeks, as shown in the final two columns of Table 22. As previously mentioned, VHA patients who have waited for an appointment for more than four weeks may seek care from a non-VHA provider, with the VHA covering appointment costs. Thus, we consider patients leaving the queue if they wait more than four weeks with some probability of 0.5 and 1.0. In each of these scenarios, far fewer patients are seen overall because so many patients have left the system and wait time is near zero.

4.4. Conclusions

COVID-19 has caused significant disruptions to healthcare operations, including reduced capacity for non-emergency procedures like endoscopy. The simulation model described in this chapter can help clinical decision-makers understand how pandemic-influenced reduced capacity for non-emergency procedures could impact patient wait time and other important metrics. Further, decision-makers can adjust their reopening plans and triage strategies to help achieve meaningful outcomes for patients, while ensuring patients are seen in a clinically beneficial and patient-centered timeframe.

Our model does not aim to find the “best” strategy to mitigate patient backlog for endoscopy visits in the VHA. Rather, it provides additional information in the decision-making process of VHA leaders in their pursuit of the best possible patient care. If their goal is to have the most patients possible receive endoscopy visits within the simulation time period, the Overtime strategy will prove most beneficial of the strategies reviewed. However, because this strategy alone does not triage lower-urgency patients, the number of patients waiting beyond four weeks is high. To ensure average waiting time remains relatively low, both overall and within each patient category, one or both of the Exchange and Extend strategies may be included so screening and/or low-risk surveillance patients can be triaged to an alternative form of care.

VHA leaders should consider that triage strategies may not be universally accepted by patients. For example, a low-risk surveillance patient may not want to defer their colonoscopy for two years, preferring instead to be seen as soon as possible. Additionally, the VHA may not want to shift operational or financial resources to FIT or deferred colonoscopy visits as is required in the Exchange and Extend strategies, respectively. For these reasons, the VHA should consider potential outcomes under partial uptake of patient triage strategies, as outlined in Tables 19 and 20.

This chapter's model has limitations. First, the prioritization structure of patient visit assignments is relatively rigid in its hierarchy of patient risk categories. In reality, a high-risk surveillance patient who has been waiting to be seen for 12 weeks may be prioritized over a newly-arrived diagnostic patient. However, within the confines of the reduced capacity due to COVID-19, the assumption of a strict hierarchical prioritization is more reasonable.

An additional limitation is that our model is strict in strategy implementation. Analyses assume that a strategy carries throughout the entire simulation period, even if patient backlog has been relatively well-resolved. Given that the impact of COVID-19 has been somewhat unpredictable and such strategies may need to be used longer than expected, this limitation seems acceptable. Further, because the two patient triage strategies, Exchange and Extend, are both clinically-proven alternatives to endoscopy visits, one can assume that continuing using these strategies after backlog has been resolved will not lead to patient harm.

Each strategy discussed requires consideration from the VHA in *how* it is implemented. Specifically, the VHA must weigh the trade-offs between the reduction in patient backlog and each strategy's additional outcomes. With the Exchange strategy the VHA needs to ensure it has the resources and capacity to handle increased FIT processing, as well as the increase in number of diagnostic patients needing colonoscopy visits following a positive FIT result. Under Extend, the VHA is delaying a subgroup of patients from receiving colonoscopy visits for two years. This reduces current patient backlog but could lead to subsequent increased system-level burden and/or patient backlog if the future operational state is unable to handle the deferred patients well. The Overtime strategy widely benefits patients by allowing more patients to be seen and reducing wait time, but may negatively impact clinicians and other staff due to burnout and/or increased exposure to risk of COVID-19 infection.

The simulation model described in this chapter could be applied to other non-emergency outpatient procedures, particularly those that include a range of patient categories who may utilize those procedures, including primary care annual physical examinations, dental visits, or other cancer screening/diagnostic procedures. Further, this simulation model could be used during non-pandemic time periods to examine impact of new policies or triage strategies.

Finally, while our model inputs were specific to the VHA location in Ann Arbor, Michigan, the structure and logic of the model can be applied to other VHA locations across the country. We have begun working with the national GI office within the VHA to apply these strategies in different settings that may have different relationships between patient arrivals and capacity or different rates of reopening capacity. With this cross-clinic comparison, we may identify how various strategies or combinations of strategies can impact clinics with different types of parameters.

Chapter 5. Assessing the Impact of Incorporating Predictive Modeling into Chronic Liver Disease Appointment Decision-Making

Chronic liver disease (CLD) is a potentially fatal disease, and it is sometimes difficult to detect because of its long asymptomatic phase. A new tool known as analytic morphomics uses predictive modeling to diagnose CLD earlier and more accurately. In this chapter, we use discrete-event simulation to model how patients referred for CLD could be assigned to appointments based on the severity of patients' disease under various clinical decision models, including analytic morphomics. We consider each decision model's predictive power and policies about collecting patient data used for model inputs. This work can help clinics assign CLD patients more accurately to an appointment type that best aligns with patient needs.

5.1. Problem Background

Predictive modeling broadly describes a mathematical methodology that considers a set of inputs and uses historical relationships to estimate outcomes of interest. The relationships in these models are computationally driven by statistics. Engineers often design the structure of the model, including how the components interact. Predictive modeling has been applied to several domains, including healthcare.

An objective of using predictive modeling is to improve precision in decision-making. For example, a predictive model could use data from a hospitalized patient's medical record to determine how likely they are to be readmitted if they are discharged today versus tomorrow. (84) Clinical providers can use this information in discussions with patients about discharge decisions, which can lead to improved outcomes.

However, little work has been done to examine how using these predictive models in practice impacts system-level operations and outcomes. If a hospital were to implement the readmission prediction model described in the previous paragraph, using this model may lead to an increase in the average hospital length of stay in efforts to minimize future readmissions. With many patients having longer stays, the hospital may see overcrowding *now*, which could be operationally challenging, as well as potentially harmful to patients.

This chapter explores system-level outcomes of incorporating predictive modeling in decision-making. Specifically, we use discrete-event simulation to examine how a Veterans Health Affairs (VHA) hepatology clinic could use predictive modeling outcomes to determine a patient appointment type when patients are referred for chronic liver disease (CLD), compared to other non-predictive diagnostic models. We consider how using predictive modeling changes outcomes based on current state appointment assignments and how the clinic may need to adjust operations to accommodate those changes. We also explore how the characteristics of the predictive model could impact outcomes by analyzing results when models' predictive powers are altered.

5.1.1. Predictive Modeling and Medical Decision-Making

Clinicians and other healthcare leaders have been utilizing computers and other technology to support and/or guide their decision-making processes since the 1950s. (85–87) Computers are often used in healthcare to improve patient outcomes by improving precision of diagnoses or treatment planning or to improve system-level outcomes by increasing operational efficiency. In these capacities computers and other technological tools supplement human-level decision-making by confirming or questioning a clinician's medical decision given some clinical information. An example of this would include a flag in a patient's electronic health record alerting a clinician that two prescribed medications may have a harmful interaction. (88) Additionally, technology may be used to expedite the processing of information in the form of complex algorithmic calculations.

Predictive modeling in particular has been commonly used in guiding diagnosis and treatment, especially in classification. Classification is a process of putting objects – in this case, the objects are often patients – into predefined categories based on the objects' characteristics. For example, a patient's glucose levels can be used to categorize their diabetes status into three buckets: normal (no diabetes), prediabetes, and diabetes. (89) We thus use quantitative patient information to *classify* the patient as one of three categorical diagnoses of this chronic disease.

As a tool, predictive modeling can be especially helpful in medical decision-making because it has the potential to prevent patient harm, improve clinical outcomes, and improve value. In many contexts, predictive modeling may reduce the number of diagnostic or screening tests needed to accurately diagnose a patient for given condition, which reduces the likelihood of a patient incurring harm during that testing. (90) Under some scenarios, predictive modeling may alternatively *increase* the amount of testing performed. Additionally, predictive modeling may improve the precision of those results, which can improve treatment planning and lead to better patient outcomes. (91) Finally, because fewer diagnostic tests may be needed and care is more personalized to a specific patient, a system may reduce unnecessary or wasteful procedures, thus decreasing costs and improving the value of care provided. (92)

Nevertheless, when predictive models are considered in healthcare, the impact is generally focused on improving outcomes for a specific patient or patient group by indicating that diagnostic accuracy for a given disease is improved by some percentage. As we discuss throughout this chapter, more work is needed to understand broader system-level outcomes of implementing predictive modeling into standard care pathways. This chapter will help us explore how incorporating predictive modeling may impact system-level operations, as well as how changing a model's predictive power impacts the larger system. This type of exploration can be helpful in determining how predictive models could impact access to care.

5.1.2. Chronic Liver Disease in the VHA

Chronic liver disease (CLD) is a condition in which a patient's liver functioning has progressively deteriorated for at least six months. CLD could be caused by many related conditions, including chronic hepatitis infection, excessive use of alcohol, non-alcoholic fatty liver disease, and genetics. Individuals with CLD are treated by hepatologists, physicians who specialize in diseases of the liver. (93)

CLD patients at the Ann Arbor Veterans Health Affairs (VHA) hepatology clinic are referred for consultation by non-hepatology providers, usually primary care providers (PCPs). PCPs commonly refer patients for CLD consultation based on risk factors including Hepatitis C infection, liver masses found in imaging, and cirrhosis. (94) Cirrhosis is scarring of the liver tissue and it indicates late-stage, more severe CLD. (93) Cirrhosis is diagnosed by a PCP using blood tests and imaging tests, like computed tomography (CT) or magnetic resonance imaging (MRI). (95) CLD has a long asymptomatic phase, making it difficult to precisely diagnose early in disease onset.

Severity of CLD can be categorized in multiple ways; within this chapter we consider three stages: mild, moderate, and severe. Mild CLD indicates liver disease but no cirrhosis present. Moderate CLD indicates liver disease with some cirrhosis. Severe CLD indicates liver disease with decompensated cirrhosis. A patient with mild or moderate CLD who is left untreated is likely to progress to a more severe disease state. In our simulation model, we consider a cohort of patients referred to a hepatology clinic, thus they are likely to have at least mild CLD. Thus, we do not consider patients with no CLD.

In the current state, when a CLD patient is referred to the hepatology clinic of the Ann Arbor VHA, a trained non-clinician scheduler will determine if and how the patient receives a consultation, based on the patient's clinical information and perceived CLD severity. Patients who seem to have severe CLD are most likely to receive a consultation, which is performed during an in-person appointment with the hepatologist.[2] Patients perceived to have mild CLD may not receive an appointment, and if they do it would more likely be an electronic consult (e-consult), which is an asynchronous provider-to-provider communication within an electronic health record. (96) Patients who are perceived somewhere between mild and severe CLD (within a group of "moderate" CLD patients) generally receive some type of appointment, but it could be in-person, e-consult, or a virtual and synchronous visit. Note that within this specific clinic, most referred CLD patients are nearly always offered *some* type of appointment so that patients feel they are not being neglected and satisfaction is maintained.

5.1.3. Evaluating Chronic Liver Disease

Fully understanding a patient's chronic liver disease severity can be difficult, especially in early-stage CLD. While liver biopsy remains the gold standard for diagnosing most hepatological diseases, biopsy is invasive and may lead to patient harm. (97) Several models, algorithms, and scoring systems have been developed to assist clinicians, schedulers, and others in better understanding a patient's true disease state without biopsy. For our work, we will consider three methods for evaluating CLD status: FIB4 index, Child-Turcotte-Pugh (CTP)

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[2] During the COVID-19 pandemic, appointments typically performed in-person may have been conducted virtually.

score, and analytic morphomics. The first two methods, FIB4 index and CTP score are more commonly used in current practice and yield an objective value to *descriptively indicate* a patient's current disease state. Analytic morphomics is a newer method that uses machine learning methods to more accurately understand a patient's current disease state, while also *predicting* currently asymptomatic CLD.

5.1.3.1. FIB4 Index

The FIB4 index uses *four* patient data elements (patient age, platelet count, and two different liver enzyme levels, aspartate aminotransferase and alanine aminotransferase) to predict *fibrosis*, an elevated level of scar tissue in the liver. (97) These data are combined in the following formula to calculate FIB4 index:

$$FIB4\ Index = \frac{age * (asparate\ aminotransferase)}{(platelet\ count) * \sqrt{(alanine\ aminotransferase)}}$$

The resulting value indicates the predicted level of fibrosis on scale between 0.2 and 10. Patients with a FIB4 index less than 1.45 are highly likely to have mild CLD and a FIB4 index over 3.25 indicates high likelihood of severe CLD. (97) An advantage of this method is that most patients referred to the hepatology clinic for CLD have the necessary data to calculate the FIB4 index. (98) A disadvantage of the FIB4 index is that a value between 1.45-3.25 does not yield a conclusive indication of a patient's CLD state.

5.1.3.2. Child-Turcotte-Pugh Score

The Child-Turcotte-Pugh Score (CTP Score) helps classify patients' liver disease and cirrhosis progression using five clinical features: bilirubin levels, albumin levels, prothrombin time (related to blood clotting speed), ascites (fluid build-up), and hepatic encephalopathy (loss of brain-function due to liver disease). (99) These features are combined in the following table that indicates a number of points a patient accrues based on their features:

Table 23. Calculation of the Child-Turcotte-Pugh Score

Factor	**1 point**	**2 points**	**3 points**
Total bilirubin (µmol/L)	<34	34-50	>50
Serum albumin (g/L)	>35	28-35	<28
Prothrombin time international normalized ratio	<1.7	1.71-2.30	>2.30
Ascites	None	Mild	Moderate-Severe
Hepatic encephalopathy	None	Mild to Moderate	Severe

The sum of the points for each feature result in a CTP score. A CTP score of 5-6 indicates mild to no CLD, a score of 7-9 indicates moderate CLD, and a score over 9 indicates severe CLD. (99) Unlike the FIB4 index, the data required for the CTP score is not as commonly found within patient records, so providers may need to require additional testing/data collection to calculate a CTP score.

5.1.3.3. Morphomics

The FIB4 index and CTP score both use clinical data as inputs to calculate a quantitative value to guide clinicians in diagnosing CLD, however neither of these models would be classified as a "predictive model." In contrast, a recently developed tool, morphomics, uses predictive modeling in guiding CLD diagnosis.

The morphomics model (or, more completely, "analytic morphomics model") is a logistics regression model with elastic net regularization. The primary feature of the morphomics model is a computed tomography (CT) scan, but the model also considers several other values from a patient's medical record including patient demographics and laboratory test values. The morphomics model can also include the results of other hepatologic algorithms, like the FIB4 index, as a feature used in predicting CLD severity. (100) The morphomics model classifies patients into non-cirrhosis (mild CLD) or cirrhosis (moderate or severe CLD) categories.

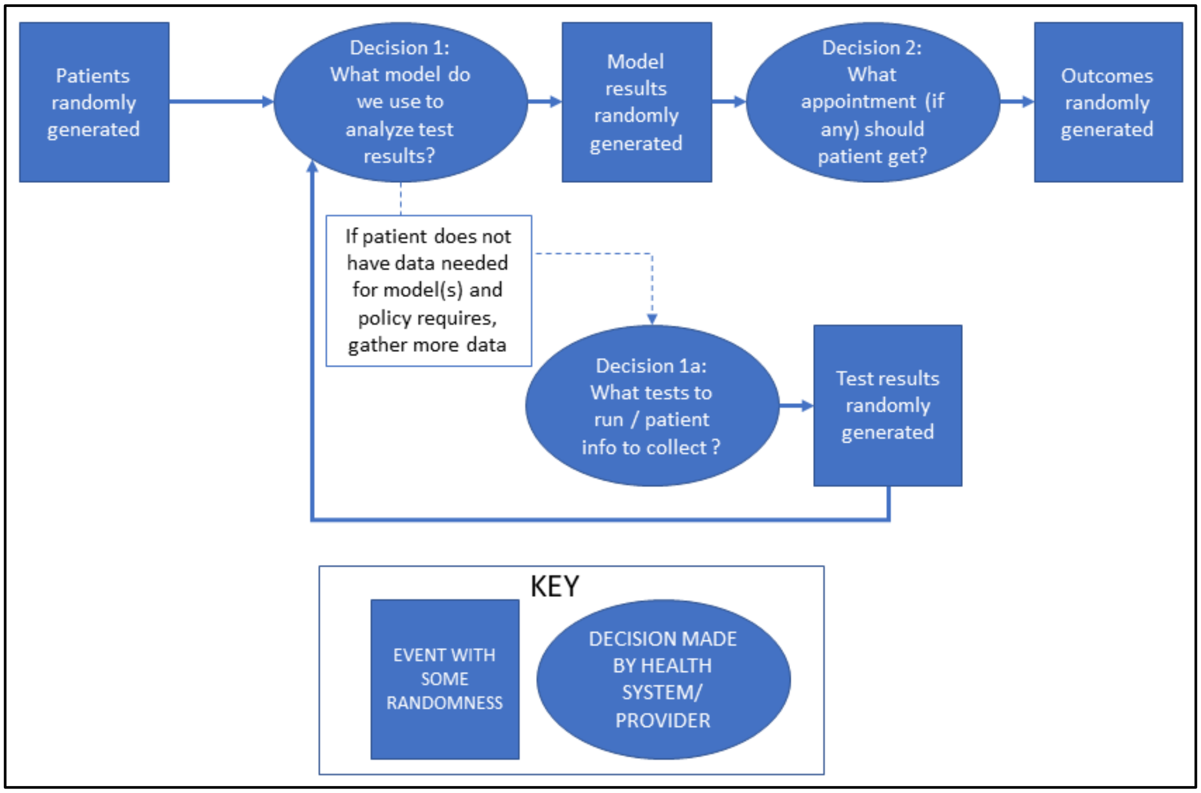
A key advantage of using the morphomics model is that it is effective at detecting CLD early in disease onset. A disadvantage of the morphomics model is that it requires a patient having a CT scan within the past 6 months, as well as many recent test results. While providers who would like to use morphomics in better understanding a patient's true CLD severity can refer a patient for a CT scan and other additional testing, these referrals can be costly and burdensome for the patient. We explore the trade-offs of this and other considerations in our simulation model.

5.2. Methods

We developed a discrete-event simulation model to consider various policies (outlined in Section 5.2.1) to consider CLD appointment decision-making using various clinical decision models, including the FIB4 index, CTP score, and morphomics. We compare these policies under several scenarios, as detailed in Section 5.2.2.

Our model includes a pathway as outlined in Figure 1. In each replication a number of patients "arrives" to indicate they are being referred to the VHA hepatology clinic. For the analyses presented in this chapter, we set this number to be 77,597, which represents the number of patients who visited the Ann Arbor VHA Hepatology Clinic from 2008-2014. Each patient who arrives has some probability of having the tests and other data required to run each of the three clinical decision models. Each patient also has some true disease state which is hidden from the perspective of the appointment decision-maker.

Figure 7. Chronic Liver Disease Patient Flow



Depending on the policy being used and the availability of data for a given patient, a decision model is used to estimate a patient's disease state (Decision 1). The results of this decision model are the patient's predicted disease state and a binary indicator of confidence in that prediction. Depending on the policy and what data the patient currently has, a patient may be "sent" to gather additional tests or other data, which may improve the confidence in the predicted disease state (Decision 1a). If a patient is sent for additional data collection, we track the additional tests performed and then the patient returns to Decision 1.

After decision model results have yielded sufficient confidence according to our policy, a decision is made about what type of appointment a patient should be offered (Decision 2). As discussed in Section 5.1.2., a patient's clinically-ideal appointment is based on the patient's true disease state, with severe CLD patients indicating a need for in-person appointments and moderate CLD patients being referred for telehealth appointments. Mild CLD patients are recommended less intensive appointments, like e-consult. In our simulation model we also consider another low-intensive “appointment” type called population management. Population management involves the referring provider, often a primary care practitioner, to monitor a patient’s health over time instead of the patient receiving a hepatology appointment. Population management is not commonly used in VHA referring clinics currently, but our clinical collaborators indicated it could be a reasonable option for mild CLD patients and should be included in our simulation model. Because population management is a less-intensive appointment, we only recommend a patient for this type of appointment if we have high confidence in our prediction of their disease state. For our model, we consider any prediction that uses morphomics to infer high confidence. Thus, any patient who is predicted to have mild CLD using a decision model that includes morphomics is recommended for population management; any patient predicted to have mild CLD using another decision model is referred to an e-consult.

Once a patient has been recommended for an appointment, the patient’s true disease state is “revealed,” allowing us to calculate metrics using various policies under difference scenarios. Metrics include how often true disease state was accurately predicted, number of various appointment types provided, and how often patients were sent to gather additional test results or other information. We consider metrics across all disease states and also stratified by disease state to examine if various policies are more helpful for certain patient subgroups.

Input data for our simulation model comes from previously published studies on CLD decision models and operational data from the Ann Arbor VHA Hepatology Clinic. An overview of the input data is outlined in Table 24.

Table 24. Baseline Input Parameters

Parameter	Value
Number of patients	77,597*
Proportion of true disease state among patients	
Mild CLD	89.6%
Moderate CLD	5.8%
Severe CLD	4.6%
Probability that patients arrive with tests to run decision model	
FIB4 Index	79%
CTP Score	35%
Morphomics	29%

* Represents CLD patients from 2008-2014

We use several clinical decision models as discussed in previous paragraphs. The predictive accuracy of each of those models is incorporated into our simulation using a disease prediction matrix, as exemplified in Figure 8. See Appendix B for all baseline values for each decision model. Broadly, these matrices indicate the probability a disease state will be predicted, given a patient's true disease state, for each decision model (FIB4, CTP, and morphomics). We also include matrices for using two or three decision models when patients have the data needed for more than one decision model and the policy permits combining decision models. We assume that when more than one decision model is used to predict a patient's disease state, the combined decision models will be superior to either single model. For example, using both a FIB4 index and a CTP score will yield more accurate predictions than using FIB4 index or CTP score alone.

Figure 8. Sample Disease Prediction Matrix

		Predicted State		
		Mild CLD	Moderate CLD	Severe CLD
Actual State	Mild CLD	A_1%	B_1%	C_1%
	Moderate CLD	A_2%	B_2%	C_2%
	Severe CLD	$(1-A_1-A_2)$%	$(1-B_1-B_2)$%	$(1-C_1-C_2)$%

In addition to prediction matrices for our three clinical decision models (FIB4, CTP, and morphomics) and their combinations, we also include a “general prediction matrix” (also in Appendix B) which indicates how the disease state for patients referred for CLD may be estimated in the absence of clinical decision models. The values in all of our prediction matrices are provided by the Ann Arbor VHA Hepatology Clinic, based on a population of referred CLD patients.

5.2.1. Policies

Several policies could be used to examine the impact of access when incorporating predictive models into CLD appointment decisions. In this chapter, we will focus on six main policies: (A) no decision models used, (B) no additional testing, (C) FIB4 testing required, (D) CTP testing required, (E) morphomics testing required, and (F) all testing required. Regardless of the policy in place, we assume that if a patient has the testing required for a decision model and the policy permits that model can be used, we always include it in our disease prediction.

Under Policy A, we only use the general prediction matrix to determine a patient’s predicted disease state, ignoring any tests or data the patient has. Policy A is largely used as a reference case for our other policies.

Under Policy B (no additional testing), we can only use the information (demographics, lab/imaging results, etc.) that a patient has when they are referred to hepatology for CLD. Under this policy, a patient’s disease state is predicted using any one (or more) of the decision models (FIB4, CTP, or Morphomics) if a patient has the required data to run the decision model(s). If the patient does not have the required data to run any decision model, we use the general prediction matrix to estimate disease state.

Under Policies C-E, patients who are referred to hepatology for CLD are required to obtain one set of tests to satisfy needs for a given decision model, depending on which policy is implemented (FIB4 under Policy C, CTP under Policy D, and Morphomics under Policy E). Under each of these policies, our simulation tracks the number of patients who are required to obtain additional testing. In reality, this required testing would necessitate additional patient appointments, adding to patient burden and increased operational needs for the referring clinic. However, this additional testing can improve appropriateness of appointment decisions, which may improve patient clinical outcomes.

Note that under Policies C-E, a patient may arrive with the necessary testing to run one clinical decision model but may have to return for additional testing if it is not the decision model highlighted in the specific policy. For example, if Policy E is enforced, a patient is required to have morphomics testing. If a patient arrives with the necessary testing to run FIB4, they are still required to obtain morphomics testing, but when we use the decision models to predict the patient's disease state, we can use both FIB4 and morphomics, yielding a higher predictive power than morphomics alone.

Under Policy F, patients are required to obtain testing for all three decision models and are returned to gather any testing that they do not have when referred. In this policy, the disease prediction matrix that incorporates all three decision models will always be used.

5.2.2. Scenarios

In our analysis, we consider three scenarios: (1) baseline, (2) altering morphomics predictive power, (3) altering true disease state distribution. Scenarios 2 and 3 act as sensitivity analyses to help us understand how changing the assumptions and inputs of our model can impact outcomes.

Scenario 1 (baseline) examines the five policies using baseline parameters, as outlined in Table 24, as well as the prediction matrices as outlined in Appendix B. Scenario 2 (altering morphomics predictive power) examines our five policies, but with lower/higher predictive power for our morphomics decision model. In this scenario, we increase/decrease the values in prediction matrices that use morphomics to indicate how changing the accuracy of a predictive model has larger impacts. Scenario 2 values are conceptual but allow us to better understand the broader impacts that may arise from improving or degrading a predictive model's power. Improvements in predictive power could arise through considering previously unutilized features in the analytic morphomics model, while lower predictive power may arise from imprecise test results used as input data for the model.

In scenario 3 (altering true disease state distribution), we increase the proportion of patients who have moderate and severe CLD from our baseline distribution. This allows us to understand the impacts of using predictive modeling in appointment decision-making in a population with more moderate/severe CLD (and thus less mild CLD).

5.3. Results

5.3.1. Baseline Results

Baseline scenario results are presented in Tables 25 and 26. Compared to Policy A, in which we ignore any patient data and use a general prediction matrix to determine a patient's disease state, all policies show improvement in percentage of patients' true disease states correctly predicted. Under Policy B, in which we use any available patient data to inform our prediction but do not require any additional testing, the overall percentage correctly predicted is 64.3%, compared 40.3% in Policy A. For Policies C-E, in which one decision model's set of tests is required, this percentage continues to increase, with Policy E having the highest percentage at 87.4%. If testing is required for all decision models (Policy F), we see the highest percentage of correctly predicted disease state at 93.5%.

The baseline results presented thus far are relatively straightforward; as we use models with higher predictive power, we improve the percentage of patients' disease states correctly predicted. We use these results as validation of our model logic, as well as a foundation for comparing the analyses discussed in subsequent sections of this chapter.

Table 25. Percentage of Correctly Predicted True Disease State under Baseline Conditions

	Percentage of True Disease State Correctly Predicted			
Policy	**Mild**	**Moderate**	**Severe**	**Overall**
A. No Testing Used	40.1%	34.4%	50.8%	40.3%
B. No Additional Testing	66.5%	41.0%	60.8%	64.7%
C. FIB4 Required	67.5%	40.4%	61.1%	65.7%
D. CTP Required	87.4%	44.1%	53.5%	83.2%
E. Morphomics Required	88.5%	69.2%	89.2%	87.4%
F. All Testing Required	94.9%	75.1%	90.0%	93.5%

In Table 26, we can see a high-level perspective of how various policies impact system-level access. For example, under Policies B-D, some patients have disease state predicted using decision models that include morphomics and others do not, thus e-consult and population management are both used as appointment recommendations for patients predicted to have mild CLD. In Policies E and F, all patients use a model that includes morphomics, thus all patients who are predicted to be mild CLD are recommended population management. Table 26 also indicates the number of patients who would need to return for additional testing under the various policies, with Policy F requiring the most additional testing. Note that the number of patients requiring additional testing will not change in future scenarios and are only reported here, but one can be assume similar values in other scenarios.

Table 26. Appointments Needed and Additional Testing Required under Baseline Conditions

	Appointments Needed				*Patients Requiring Additional Testing*		
Policy	**Pop. Mgmt.**	**E-Consult**	**Telehealth**	**In-Person**	**FIB4**	**CTP**	**Morph.**
A. No Testing Used	0	30,054	26,894	20,649	0	0	0
B. No Additional Testing	17,199	30,518	20,353	9,527	0	0	0
C. FIB4 Required	17,461	31,028	20,426	8,682	16,435	0	0
D. CTP Required	18,806	44,114	11,950	2,727	0	50,512	0
E. Morphomics Required	61,948	0	11,575	4,074	0	0	55,902
F. All Testing Required	66,484	0	7,285	3,828	16,283	50,678	55,628

Taking the results of Tables 25 and 26 together, clinical decision-makers can begin to consider trade-offs between increased disease predictions from requiring more testing as shown in Table 25, and the additional testing required under various policies. For example, moving from Policy B (no additional testing) to Policy C (FIB4 required), the percentage of true disease state correctly predicted increases by only 1%, but 16,435 patients will require additional testing to calculate a FIB4 index. Moving from Policy B to D (CTP required), we see an increase in percentage of true disease state correctly predicted of nearly 20%, but over 50,000 patients will require additional testing to calculate a CTP score.

One can also consider the types of referral appointments used under various policies, especially for more resource-intensive appointments like in-person and telehealth visits. Under Policy A (no testing used), we see nearly 50,000 telehealth and in-person appointments needed. Once we begin to use some decision models (in Policy B onward), the number of needed telehealth and in-person visits decreases, while percentage of true disease state correctly predicted increases. Compared to Policy A, implementing Policy B sees an almost 25% increase of correctly predicted true disease state, a decrease of about 15,000 telehealth/in-person appointments needed, and no additional testing appointments required for patients.

5.3.2. Altering Morphomics' Predictive Power Results

We next examine results when the predictive powers of our morphomics-based models are changed, including one scenario in which predictive power is lower and another in which it is higher. The matrices used in these scenarios are included in Appendix C. In general, we decrease/increase correct classification probabilities in these matrices by 5%. An exception to this change is any morphomics-based models that also use CTP score, which have a high probability of correct classification of mild CLD; these values are changed by just 1%.

Table 27 presents percentage of patients' correctly predicted true disease state when the morphomics' predictive power is decreased. Compared to our baseline scenario, all policies (except our reference policy, A) show lower percentages of correctly predicted true disease state. In Table 28, we also see small changes in the appointments needed. In particular, compared to our baseline scenario, we see an increased number of telehealth or in-person appointments needed, indicating patients are more likely to be predicted as moderate or severe CLD under these conditions.

Table 27. Percentage of Correctly Predicted True Disease State under Lower Morphomics Predictive Power Conditions

	Percentage of True Disease State Correctly Predicted			
Policy	**Mild**	**Moderate**	**Severe**	**Overall**
A. No Testing Used	40.2%	33.7%	51.3%	40.3%
B. No Additional Testing	65.6%	38.6%	59.2%	63.8%
C. FIB4 Required	66.4%	39.9%	58.9%	64.5%
D. CTP Required	86.0%	39.6%	53.5%	81.9%
E. Morphomics Required	85.4%	60.7%	84.0%	84.0%
F. All Testing Required	90.2%	65.0%	85.4%	88.5%

Table 28. Appointments Needed under Lower Morphomics Predictive Power Conditions

	Appointments Needed			
Policy	**Pop. Mgmt.**	**E-Consult**	**Telehealth**	**In-Person**
A. No Testing Used	0	30,073	26,910	20,614
B. No Additional Testing	17,010	30,299	20,991	9,297

C. FIB4 Required	17,124	30,564	21,148	8,761
D. CTP Required	17,804	44,356	12,631	2,806
E. Morphomics Required	60,230	0	13,394	3,973
F. All Testing Required	63,251	0	10,269	4,077

Alternatively, we can also consider morphomics-based models to have higher predictive power. The results of these analyses are shown in Tables 29 and 30. In Table 29, we see higher percentages of patients whose disease state is predicted correctly compared to our baseline scenario. Of note, under Policy F, in which all patients' disease state is predicted using a prediction model which incorporates morphomics, FIB4, and CTP, we see the 96% of patients' disease states are correctly predicted. In Table 30, we see that the number of telehealth appointments has decreased in all policies compared to our baseline scenario. This is largely due to our decision models more often correctly predicting mild or severe CLD in patients, thus not misclassifying them as moderate CLD.

Table 29. Percentage of Correctly Predicted True Disease State under Higher Morphomics Predictive Power Conditions

	Percentage of True Disease State Correctly Predicted			
Policy	**Mild**	**Moderate**	**Severe**	**Overall**
A. No Testing Used	40.2%	34.6%	49.9%	40.3%
B. No Additional Testing	67.6%	43.4%	60.9%	65.8%
C. FIB4 Required	67.9%	44.5%	62.3%	66.3%
D. CTP Required	87.5%	43.2%	56.0%	83.6%
E. Morphomics Required	92.4%	77.9%	94.2%	91.6%
F. All Testing Required	97.1%	80.1%	95.1%	96.0%

Table 30. Appointments Needed under Higher Morphomics Predictive Power Conditions

	Appointments Needed			
Policy	**Pop. Mgmt.**	**E-Consult**	**Telehealth**	**In-Person**
A. No Testing Used	0	30,134	26,892	20,571
B. No Additional Testing	17,967	30,546	19,761	9,323
C. FIB4 Required	18,107	30,669	20,173	8,648
D. CTP Required	19,111	44,029	11,598	2,859
E. Morphomics Required	64,544	0	9,020	4,033
F. All Testing Required	67,741	0	5,793	4,063

From this scenario's results, we see that increasing or decreasing the predictive power of morphomics-based decision models logically results in a corresponding increase or decrease in the percentage of true disease state correctly predicted. When considering morphomics-based models with decreased predictive power, policies that use these models still show higher percentages of correctly predicted true disease state, though as we see in Table 27, this value for Policy E is only slightly greater than in Policy D (CTP required). If morphomics-based models were adjusted to have increased predictive power, we see the greatest value in predicting mild and severe CLD patients' true disease state correctly (>90%).

5.3.3. Altering True Disease State Distribution Results

In our final scenario, we alter the distribution of patients' true disease state. As shown in Table 24, in our baseline, approximately 89% of patients have mild CLD, 6% have moderate CLD and 5% have severe CLD. In this scenario, we adjust this distribution to be 50% mild CLD, 25% moderate CLD, and 25% severe CLD. This adjustment allows us to examine how our policies may impact the appointments needed if the underlying patient population had more moderate/severe CLD than the original cohort.

In Table 31, we see that within each patient category (mild, moderate, and severe CLD), the percentage of correctly predicted true disease state does not change much from the baseline scenario. However, because our distribution of patients' true disease state is different from the baseline, the overall percentages are different in this scenario, with all overall percentages of correct predictions lower, apart from our reference policy, A. Because our decision models tend to predict mild CLD most accurately, this decrease makes sense. When we have fewer mild CLD patients and more moderate/severe CLD patients, our overall accuracy will decrease.

Table 31. Percentage of Correctly Predicted True Disease State under Altered True Disease State Distribution Conditions

	Percentage of True Disease State Correctly Predicted			
Policy	**Mild**	**Moderate**	**Severe**	**Overall**
A. No Testing Used	40.5%	33.8%	50.5%	41.3%
B. No Additional Testing	66.8%	40.9%	60.0%	58.5%
C. FIB4 Required	66.6%	42.0%	61.8%	59.3%
D. CTP Required	87.1%	41.5%	56.2%	68.1%
E. Morphomics Required	88.7%	69.6%	89.0%	84.0%
F. All Testing Required	95.0%	75.2%	90.1%	88.8%

Table 32 indicates the appointments needed when our true disease state distribution is altered to include fewer mild CLD patients. Under these conditions, we see far fewer patients being referred for population management and e-consult appointments, and more patients referred for telehealth and in-person appointments. This shift can be attributed to the more moderate and severe CLD patients in the cohort appropriately needing telehealth and in-person appointments.

Table 32. Appointments Needed under Altered True Disease State Distribution Conditions

	Appointments Needed			
Policy	**Pop. Mgmt.**	**E-Consult**	**Telehealth**	**In-Person**
A. No Testing Used	0	25,911	25,750	25,936
B. No Additional Testing	10,328	23,243	22,722	21,304
C. FIB4 Required	10,223	22,548	23,084	21,742
D. CTP Required	11,003	33,056	18,721	14,817
E. Morphomics Required	36,775	0	19,959	20,863
F. All Testing Required	38,659	0	18,470	20,468

The results of this scenario indicate the importance of considering the predictive power of decision models in the context of the patient population in which they are applied. When our overall patient population includes more moderate and severe CLD patients, our overall percentage of correctly predicted disease state decreases compared to our baseline scenario. This decrease is because the included decision models are generally worst at correctly predicting moderate CLD, so if we increase the proportion of these patients, our percentage of correctly predicted disease state correspondingly decreases. One could therefore consider an ideal patient population for our decision models would be one in which there are primarily mild and/or severe CLD patients.

5.4. Conclusions

As predictive modeling continues to be incorporated into decision-making about clinical appointments, healthcare leaders will need to understand how using such techniques may have a system-level impact on operations and patient access. The simulation model presented in this chapter demonstrates a tool to guide clinical decision-makers as they determine how best to incorporate predictive modeling in making decisions for patients. While we focused on chronic liver disease in this chapter, the approach presented here could be applied to other diagnoses in which patients can be classified within several categories and multiple models existing in which patient data can be analyzed.

The results of our model show that predictive modeling can be effectively used to increase a provider’s understanding of a patient’s true disease state, thus improving the appropriateness of the hepatology appointment recommended to that patient. Depending on the policy in place, patients may be required to undergo additional testing, which places burden on both the patient and the provider system. Operational and clinical decision-makers can use the simulation model results to determine a policy that balances this burden with the positive clinical impact derived from additional testing.

Policy B, which uses only the information a patient has when they arrive in the system, shows a 24.4% increase in percentage of correctly predicted true disease state compared to using no testing (Policy A) under baseline conditions. This increase in correctly predicted true disease state requires no additional testing burden, but may require a shift in the mix of appointment types to which patients are referred. To improve correct prediction of patients' true disease state even further, decision-makers could implement Policy E (morphomics testing required) or Policy F (all testing required), however this will result in increased burden from additional testing.

Our second scenario presented an analysis when the predictive power of morphomics-based models was altered. Logically, if predictive power of these models was decreased, our overall percentage of correctly predicted true disease states decreased as well, with the opposite effect if predictive power of morphomics-based models was increased. These two scenarios can help clinicians and operational leaders understand how a predictive model's power either worsening or improving can impact the overall clinic. Additionally, in our final scenario, we considered a cohort that included a higher proportion of moderate and severe CLD patients compared to baseline. This scenario demonstrated that underlying disease distribution will have an impact on the distribution of appointments needed. For example, our baseline cohort included a majority (approximately 90%) of patients with mild CLD versus moderate or severe CLD, leading to a large number of population management and e-consult appointments needed. This distribution also impacts the overall percentage of patients for whom we correctly predict true disease state.

The analyses presented in this chapter are intended provide a foundation for future work and should be considered as validation for the approach discussed to consider how incorporating predictive modeling in appointment decision-making can be modeled using simulation. A limitation of our simulation is that patients never get additional testing *after* their disease state has been predicted. In reality, if a provider were not confident about a patient's predicted disease state, the provider may send the patient for additional testing, after which a decision model with higher predictive power could be used to estimate a patient's disease state. Further, our simulation model does not consider any patient attributes aside from their true disease state and if they have the testing required for our decision models. Of course, patients have many more attributes that may impact what kind of appointment they may be recommended and/or if they should be sent for additional testing. Such attributes could include how far the patient lives from the clinical location, which could impact if they are willing to comply with requests for additional testing and/or their likelihood of attending an in-person hepatology appointment. Attributes such as distance to care should be incorporated in future iterations of the simulation model presented here. Additional features to include in future versions of this model include appointment and testing capacity constraints.

In our CLD model, patients were recommended to an appointment that is best aligned to their perceived clinical needs, based on their disease state; a severe CLD patient can most benefit from an in-person appointment, a moderate CLD patient's needs can be met with a telehealth appointment, while mild CLD patients can be effectively cared for with an e-consult or population management. However, regardless of true disease state, patients will likely derive some benefit from any appointment type. That is, a severe CLD patient can still benefit from a telehealth appointment. When considering additional applications of our approach, accuracy of disease state prediction may be more critical based on the resulting appointment decision(s). For example, in a different diagnosis, it may be critical to identify severely diseased patients to ensure they receive a specific appointment recommendation. In such a case, an effective policy will need to require that the decision model(s) used to predict a patient's disease state are highly sensitive to severely diseased patients to ensure those patients receive appropriate care.

Chapter 6. Conclusions

This dissertation demonstrated four industrial engineering-based approaches for designing healthcare systems to improve access to care for veterans. These methods can be helpful both in evaluating systems to understand current state performance as well as in designing new systems and policies that concentrate on improving access. While we focused primarily on two core methodologies, linear programming and simulation, other industrial engineering tools may also be helpful to considering this issue, including Markov processes and stochastic optimization modeling.

In Chapter 2, we presented a linear programming model to improve veteran access to screening and care for chronic eye disease. This model can serve particularly helpful for Veterans Health Affairs (VHA) clinicians and administrators as they seek to screen as many patients as possible within the VHA system, as opposed to patients receiving no screening or being screened at a non-VHA provider. A strength of our model is demonstrating how the VHA system can be redesigned to increase number of patients screened with little additional cost. The model presented in Chapter 2 outlined these effects in the state of Georgia and we have used the structure of this model to guide the VHA as they plan for expanded eye care in the Central Alabama region. This model could continue to be applied to new geographic regions and/or additional outpatient VHA services like dermatology. Further, future work could include adding greater specificity to our two-step mixed-integer program that incorporates follow-up care for those who screen positive for chronic eye disease. For example, rather than a singular probability for screening positive for any eye disease, specific probabilities could be included for several diagnoses, each with their own prevalence and required number of follow-up appointments.

Chapter 3 discussed a simulation model to incorporate patient preference for appointment modality in scheduling policies. Using gastroesophageal reflux disease (GERD) as a demonstrative example, we showed that scheduling policies can be constructed to accommodate these patient preferences. While our example showed that these patient preferences could be accommodated, other clinical contexts (different diagnoses, different patient demographics, etc.) may require an increase or decrease in the number of providers needed and/or a change in the distribution of appointment types offered by each provider. A key finding in our example was the importance of considering how interwoven primary care and specialty care can be. In our GERD example, half of the potential appointments were conducted by a primary care provider. Although GERD care may often be provided by specialty care providers (here, gastroenterologists), understanding the appointment types offered by primary care providers and how they align with patient preferences is helpful in ensuring an overall efficient system in which patients are seen in a timely manner. Future work of this simulation model may include adding additional patient demographics to more robustly incorporate patient preferences. One could also add optimization into the simulation model to determine the minimal number of appointments offered of a given type to meet patient need under constraints related to allowable wait time and number of available providers.

In Chapter 4 we developed a simulation model that considered strategies for mitigating patient backlog for endoscopy during the COVID-19 pandemic. We discussed several strategies, including (1) having some patients conduct at-home testing in lieu of a screening colonoscopy, (2) deferring patients who are considered low-risk in colon cancer surveillance for two years, and

(3) adding weekend clinic hours to increase weekly capacity. The objective of this simulation model was not to identify the *best* strategy, but rather to help decision-makers understand the trade-offs of implementing one or more of these strategies. For example, adding weekend clinic hours and incorporating no other strategies allows for the greatest patient volume to be seen over the course of our given period. However, compared to one of the first two strategies, many patients are waiting excessive amounts of time for their appointments. A clinic can likely receive the most benefit from incorporating more than one strategy but may not have the resources available to do so. This model has been used to examine VHA operations starting in March 2020, when the COVID-19 pandemic began widely impacting clinic capacity. Moving forward, we can use the model to understand how future decisions from VHA clinics can help reduce persistent patient backlog. Additionally, the simulation model can be updated to more comprehensively consider patient outcomes, including adding penalties for patients lost to follow-up when they are referred for FIT or incorporating degradation of a patient's clinical state as they are waiting in the queue.

Our final simulation model was presented in Chapter 5 and demonstrated system-level considerations for incorporating predictive modeling into appointment decision-making. In this chapter, we review how a new predictive model, analytic morphomics, can be incorporated into appointment decisions for chronic liver disease (CLD). Our simulation results indicated that clinicians could use morphomics to improve appointment decision-making. However, depending on the policy used when incorporating morphomics into this process, burden may be placed on the system and on patients to receive the additional testing required for morphomics to be used. Clinical and operational leaders must weigh this burden, as well as their capability to offer the necessary referral appointment capacity, when determining the appropriate way to bring morphomics into appointment decision-making. The simulation model presented in this chapter lays the foundation for a more detailed model of our considered application in chronic liver disease. In future versions of this simulation, features can be added to incorporate a patient’s likelihood of attending an appointment, as well as their ability to comply with additional testing requests.

When considering future work in the domain of this dissertation, a logical next step would be the incorporation of equity parameters. While the models discussed herein all aim to improve veteran access to care, they do not specifically consider health equity. The mixed-integer program in Chapter 2 included some constraints to mitigate geographical barriers to healthcare access, and the simulation models presented in Chapters 3 and 4 aimed to improve access via decreased wait time, yet model features could be added to ensure the patients who need care the most are able to receive it. Further, one should consider that as we use these models to improve veteran access to care overall, we are not doing so by highly prioritizing one patient subgroup and neglecting another.

The models presented in this dissertation are all presented with parameters to reflect operations in the VHA system. The VHA has several operational and financial structures that are helpful when using industrial engineering tools like linear programming and simulation, namely that patients often stay within the system to receive care, that costs are relatively centralized, and that providers are incentivized to coordinate with others in the system and to ensure patients receive preventive care.

The features of the VHA system allow our industrial engineering models to be easily applied, but we could extend these models to non-VHA systems by adjusting constraints and making modifications to model logic. For example, the simulation model in Chapter 4 could be adapted to reflect a non-VHA system by including a probability of patients exiting the queue to seek out-of-system care if they have been waiting longer than a given number of weeks for an endoscopy appointment and/or an additional stream of patient arrivals that represents external arrivals. Such non-VHA systems would require further details on costs, especially for providers who are compensated per patient interaction, unlike salaried VHA providers. However, as discussed in Chapter 1, access to healthcare is a national public health issue that extends beyond the VHA, so applying our models in other contexts could provide great benefit to non-veterans.

Appendices

Appendix A. Appendix for Chapter 3

This appendix includes supplementary information related to Chapter 3, including the transition probability matrix and tornado diagram abbreviation guide.

We determine a patient's next appointment/exit based on a transition probability matrix given their current appointment. Note: if a patient is currently at an appointment, they may no-show, which is indicated by the probability in the matrix of their next appointment being the same as their current appointment.

Current Appointment	Next Appointment: PCP Appt 1	PCP Appt 2	PCP Appt 3	PCP Appt 4	GI Appt1	GI Appt 2	GI Appt 3	GI Appt 4 (Endoscopy)	Prob. of Exit
PCP Appt 1	0.2	0.4	0	0	0.1	0	0	0.1	0.2
PCP Appt 2	0	0.2	0.4	0	0.1	0	0	0.1	0.2
PCP Appt 3	0	0	0.2	0.4	0.1	0	0	0.1	0.2
PCP Appt 4	0	0	0	0.2	0.5	0	0	0.1	0.2
GI Appt1	0	0	0	0	0.2	0.5	0	0.1	0.2
GI Appt 2	0	0	0	0	0	0.2	0.5	0.1	0.2
GI Appt 3	0	0	0	0	0	0	0.2	0.6	0.2
GI Appt 4 (Endoscopy)	0	0	0	0	0	0	0	0.2	0.8

The tornado diagrams (Figures 4 and 5) use abbreviated names of input variables. Abbreviations and variable descriptions are listed here, as well as the minimum and maximum values used in our sensitivity analyses:

Table 33. Tornado Diagram Abbreviations and Variable Descriptions

NumPCPs	Number of Primary Care Providers	1	4
PCPCapacity/ GICapacity	Capacity of Primary Care/GI Providers	One with 4 telehealth/ 3 F2F appointments per week; one with 2 telehealth/1 F2F	One with 4 telehealth/ 3 F2F appointments per week; one with 7 telehealth/5 F2F
NumGIs	Number of GI providers	1	4
PCPArrivals	Number of patients arriving directly to a PCP each week	3	7
GIArrivals	Number of patients self-referring to a GI provider each week	5	9
apptTimeLB	Lower bound of time range of next appointment	0 weeks	4 weeks
apptTimeUB	Upper bound of time range of next appointment	6 weeks	10 weeks
teleNearProb	Probability that patients who live "near" the clinic prefer telehealth	25%	75%
farProb	Probability that a patient lives "far" from the clinic	0%	2.8%
MaxNoShows	Maximum amount patients can no-show before being dismissed	1	5
BenignProb	Probability patients receives a healthy/benign endoscopy result	85%	95%

Appendix B: Decision Model Prediction Matrices for Chapter 5

Table 34. General Prediction (No Additional Testing) Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.4	0.35	0.25
	moderateCLD	0.33	0.33	0.33
	severeCLD	0.2	0.3	0.5

Table 35. CTP Alone Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.84	0.16	0.00
	moderateCLD	0.69	0.29	0.02
	severeCLD	0.20	0.64	0.16

Table 36. FIB4 Alone Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.45	0.40	0.15
	moderateCLD	0.17	0.30	0.53
	severeCLD	0.20	0.29	0.51

Table 37. FIB4+CTP Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.84	0.16	0
	moderateCLD	0.43	0.3	0.27
	severeCLD	0.2	0.29	0.51

Table 38. Morphomics Alone Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
Actual State	mildCLD	0.85	0.15	0
	moderateCLD	0.2	0.6	0.2
	severeCLD	0	0.15	0.85

Table 39. Morphomics+CTP Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.95	0.05	0
	moderateCLD	0.2	0.65	0.15
	severeCLD	0	0.15	0.85

Table 40. Morphomics+FIB4 Alone Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.85	0.15	0
	moderateCLD	0.1	0.7	0.2
	severeCLD	0	0.1	0.9

Table 41. Morphomics+CTP+FIB4 Decision Model Prediction Matrix

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.95	0.05	0
	moderateCLD	0.1	0.75	0.15
	severeCLD	0	0.1	0.9

Appendix C: Adjusted Morphomics-Based Decision Model Prediction Matrices for Chapter 5, Scenario 2

Note: In this scenario, the values in the General Prediction, CTP Alone, FIB4 Alone, and FIB4+CTP matrices do not change.

Morphomics-Based Prediction Matrices with Lower Predictive Power

Table 42. Morphomics Alone Decision Model Prediction Matrix with Lower Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
Actual State	mildCLD	0.8	0.2	0
	moderateCLD	0.25	0.5	0.25
	severeCLD	0	0.2	0.8

Table 43. Morphomics+CTP Decision Model Prediction Matrix with Lower Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.9	0.1	0
	moderateCLD	0.25	0.55	0.2
	severeCLD	0	0.2	0.8

Table 44. Morphomics+FIB4 Decision Model Prediction Matrix with Lower Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.84	0.16	0
	moderateCLD	0.15	0.6	0.25
	severeCLD	0	0.15	0.85

Table 45. Morphomics+CTP+FIB4 Decision Model Prediction Matrix with Lower Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.90	0.05	0
	moderateCLD	0.15	0.65	0.2
	severeCLD	0	0.15	0.85

Morphomics-Based Prediction Matrices with Higher Predictive Power

Table 46. Morphomics Alone Decision Model Prediction Matrix with Higher Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
Actual State	mildCLD	0.9	0.1	0
	moderateCLD	0.15	0.7	0.15
	severeCLD	0	0.1	0.9

Table 47. Morphomics+CTP Decision Model Prediction Matrix with Higher Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.97	0.03	0
	moderateCLD	0.15	0.75	0.1
	severeCLD	0	0.1	0.9

Table 48. Morphomics+FIB4 Decision Model Prediction Matrix with Higher Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.9	0.1	0
	moderateCLD	0.05	0.8	0.15
	severeCLD	0	0.05	0.95

Table 49. Morphomics+CTP+FIB4 Decision Model Prediction Matrix with Higher Predictive Power

		Predicted State		
		mildCLD	moderateCLD	severeCLD
True State	mildCLD	0.97	0.03	0
	moderateCLD	0.05	0.8	0.15
	severeCLD	0	0.0.5	0.95

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