

MINIMIZING HEALTH CARE SPENDING BY
OPTIMIZING CARE MANAGEMENT ACTIVITIES:
A MIXED-INTEGER PROGRAMMING APPROACH TO
MANAGING POPULATION HEALTH

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**MINIMIZING HEALTH CARE SPENDING BY OPTIMIZING CARE MANAGEMENT
ACTIVITIES: A MIXED-INTEGER PROGRAMMING APPROACH TO MANAGING
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ABSTRACT

The United States has a health care spending problem. Accounting for over 17% of our Gross Domestic Product, almost 50% more than the next high-income country, America is spending much more than what is needed. Most of this money is spent on patients with chronic conditions (84%). Furthermore, a very disproportionate 20% of spending is used for the 5% of patients with five or more chronic conditions. These complex patients have become a target for cost-savings opportunities.

Care management programs are a promising option in health care as a way to control spending for complex patients by delivering more appropriate care and reducing costly admissions and emergency department visits. While research programs have been promising, real-world programs have had a difficult time realizing cost savings. Contrasting successful and unsuccessful programs has led to the belief that programs need to be very deliberate in providing the right patients the right level of care management in order to reduce costs.

This research formulates a mixed-integer programming model to allocate a care management team's resources in order to reduce overall spending for the population. The model assesses the problem from an Accountable Care Organization lens, using a care management team to match cohorts of patients within a set population to deliver the best intervention protocol from an array of options. The model is then refined to specifically match the LIGHT2 program at the University of Missouri Health Care. The data preparation needs are then addressed, specifically in relation to the LIGHT2 program.

Chapter 1 Introduction

1.1 Introduction

As health care spending in the U.S. continues to increase, hitting 17.5 percent of GDP for the first time ever in 2014,¹ there continues to be pressure on the industry to find ways to reduce costs while improving quality. This pressure comes from the consistent analysis that the U.S. performs poorly in health care among high-income countries. In 2013, the U.S. spent almost 50% more on health care than the next highest country. The spending has not paid off. Among these high-income countries, the U.S. has the lowest life expectancy, highest mortality rates, and highest percentage of people over 65 with two or more chronic conditions.^{1,2}

The silver lining is that government and private payers are attempting to address the issue by changing their payment strategies. Payers are switching from the traditional fee-for-service format, where providers received payments based on volume alone, to value-based or outcomes-based strategies. Changing the payment model is meant to better align financial incentives with quality care. One of the popular models that Medicaid is offering is called an Accountable Care Organization (ACO). ACOs are meant to better control costs by shifting some of the financial risk to health care providers.^{3,4} Under this model, providers are essentially given one lump-sum to manage a patient population. If providers cannot control costs, they will not be able to remain profitable.

One of the biggest drivers of the cost and quality issues in the U.S. is managing chronic diseases. In 2010, 84% of health care spending in the U.S. went towards patients

with chronic diseases. Even more concerning is the greater disproportion in spending seen by the five percent of the population living with five or more chronic conditions whom account for 21% of all health care spending. As patients take on more chronic conditions, the costs associated with managing their health would be expected to rise as more prescriptions are prescribed and regular outpatient visits are scheduled. However, research has shown that these patients' costs are far greater than what is clinically expected. For example, one area of wasteful spending for this group is the number of unnecessary hospitalizations, as measured by whether or not timely outpatient care could have prevented the hospitalization, which drastically increases with the number of chronic conditions.⁵

As providers prepare to operate under these new terms, increasing attention has been given to those complex patients who consume large amounts of health care. Termed "super-utilizers,"⁶ there is a growing popularity to utilize care management to reduce costs for these complex patients. By providing additional support not traditionally found in the health care system, care management programs can stabilize these patients and reduce spending by eliminating the unnecessary or inappropriate emergency department visits and hospitalizations that plague complex patients.

While the concept is easy to understand, the real-world applications of these programs have had mixed success in bringing these savings to fruition.^{7,8} However, there are examples that have demonstrated savings, especially among research projects. As a result of these experiences, patient and intervention selection have been recognized as playing a key role in the effectiveness of such programs.⁹⁻¹⁴

To that extent, a Super-Utilizer Summit held in 2013 discussed trends and strategies for these super-utilizer care management programs. The common theme from the Summit indicated that programs were having success, but only when they were extremely selective with which subpopulations of super-utilizers received select interventions. Furthermore, they indicated that identifying the right intervention for the right super-utilizer patient is akin to the “holy grail.”¹⁰

In this paper, a mathematical model is presented that can examine how to best allocate care management resources. Specifically, a mixed-integer program is used to identify patient-intervention combinations that result in the largest return on investment.

1.2 Background

1.2.1 Care management in the United States health care system

Traditionally, health care services in the United States have been tailored to manage acute problems. The result of this is that each part of the system operates largely independent of each other.¹⁵ For patients with chronic conditions who, by definition, require ongoing care, this can cause suboptimal outcomes as patients are required to connect the dots between the different care facilities they interact with regularly. As briefly discussed in the introduction, these suboptimal, or “triple failure,” events, as coined by Lewis et al.,⁹ have been shown to be more likely and costly among complex patients with multiple chronic conditions.^{15,16} Care management is one of the most popular and widely explored strategies to reduce spending by optimizing the care

of these complex patients.^{17,18}

In the past two decades, there have been many programs that attempted to provide better care to patients with chronic conditions currently being underserved. Some examples of the various types of programs used are: disease management, transitional care, care coordination, care management, case management, super-utilizer programs and complex care management. While all have unique aspects, they also contain a lot of overlapping characteristics.

The first three, disease management, transitional care, and care coordination have specific differences that are worth mentioning. Disease management typically refers to creating care plans centered around a single chronic disease. This approach was popular when providers first started creating programs to manage chronic diseases. However, as it has become known that patients with multiple chronic diseases are very common, programs have shifted focus away from disease management, or disease-specific programs.⁷ Transitional care programs are programs that aim to ensure coordination of services as patients transition from one setting to the next. Unlike many of the care management programs, transitional care programs are designed to have a short duration.¹⁹ Lastly, care coordination is less a specific intervention and more an overarching term that refers to activities that provide the necessary communication throughout the system.²⁰

The remaining terms are all very similar to or fall under the umbrella of care management. According to the Center for Health Care Strategies (CHCS), care management is defined as:

“Care management programs apply systems, science, incentives, and information to improve medical practice and assist consumers and their support system to become engaged in a collaborative process designed to manage medical/social/mental health conditions more effectively. The goal of care management is to achieve an optimal level of wellness and improve coordination of care while providing cost effective, non-duplicative services.”²¹

For the remainder of this paper we’ll use the CHCS’ definition of care management as it provides an appropriate lens under which the goal is to seek optimal care with the greatest efficiency without limiting the range of patients or interventions to be used. Within this definition, care management programs can largely be classified on the following three characteristics: delivery setting, patient selection criteria, interventions used.

First, delivery settings are the places where the program is housed. Some common settings that exist are primary care, vendor supported, hospital-to-home, home-based, and ambulatory intensive care units. Each setting has pros and cons. The primary care setting is widely popular based on the Chronic Care Model and the ideology that care coordination should stem from a primary care office but is currently lacking evidence of it yielding cost-savings. Hospital-to-home, conversely, is managed at the hospital and has great potential in reducing readmissions. Ambulatory intensive care units are essentially a primary care clinic that only sees complex patients and has many needed services on-site.^{7,17,22}

Secondly, patient selection criterion is the identification or targeting strategy for enrolling patients into a program. The selection criterion used can be classified as quantitative, qualitative, or hybrid. Within the quantitative category, criterion can be

based on prediction models that estimate future costs, more simplistic techniques such as the number of visits in a given historical time frame, or can be based on a criteria of administrative data such as diagnosis codes to identify complex patients. Again, each have advantages and disadvantages.²³ Within this topic, there is a growing base of literature identifying that patient selection needs to consider factors related to how likely a patient is to be impacted from the program's interventions.^{9-13,24-27}

Lastly, programs can be classified based on the interventions they provide and personnel utilized. Common interventions include assessing risks and needs, developing care plans, coaching patients on disease management and recognizing worsening symptoms, continued follow-ups with patients, and coordinating doctor visits and other needs. Most programs consist of a care team, with members from different backgrounds collaborating. Among these teams there may be psychiatrists, pharmacists, social workers, and health coaches, among others.²² Related to the team make-up is the team's case load, which can vary substantially across programs.^{17,22} Similarly, programs may have collaborations that allow further services. A few more unique interventions being deployed are 24/7 access, providing housing-assistance, and conducting skill-based learning for targeted groups.^{17,28,29}

1.2.2 LIGHT2 care coordination program

The motivation for this research stemmed from collaboration with the LIGHT2 care coordination program at the University of Missouri Health Care (UHMC). The LIGHT2 program was a CMS-funded innovation project to provide care coordination to Medicare

and Medicaid beneficiaries while utilizing technology in ways not yet seen in the care coordination domain. The program consisted of 25 registered Nurse Care Managers (NCMs) to provide the care coordination. In addition, UHMC leveraged their partnership with Cerner Corporation through the Tiger Institute to build a documentation system. This system allowed the NCMs to document what care coordination activities they were providing to patients and how long the activities took.³⁰ As a result, one of the outcomes of this program was a trove of intervention-specific data on care coordination activities.

1.2.3 Operations research and linear programming

Operations research is the field of study concerned with finding an optimal solution to a problem under a given set of circumstances. Originally developed to aid in strategic planning and decision-making during World War II, after the war, academia continued to develop the theory and methods while expanding their problem scope beyond military planning. Today, operations research is used by businesses and governments around the world to help run efficient organizations^{31,32}.

Generally, problem formulation involves three components: decision variables, an objective function, and constraints. The decision variables are the items in the model that can be adjusted to find an optimal solution. The objective function is the metric that aims to be optimized, such as maximizing profits or minimizing costs. Finally, the constraints are the items that limit the optimization of a problem, such as the amount of resources available^{31,32}. Given this problem framework, operations researchers have a

wide variety of mathematical models and statistical analyses they use to maximize or minimize the objective function for a given problem.

One of the most popular tools to solving these optimization problems is linear programming, which was first introduced in the early 1940s by Dr. George Dantzig.³³ Linear programming has two very appealing characteristics. First, there are only three possible outcomes for a linear program: the problem is infeasible, the problem is unbounded, or there is a unique optimal solution value. Thus, we are guaranteed to be able to find the optimal solution value for a feasible and bounded problem. The second appealing characteristic is that linear programming naturally provides a wide array of sensitivity analysis tools. Therefore, while the model requires discrete values of data, which is not typically representative of the real world, the sensitivity analyses allow the researchers' insight into the range of values certain data parameters can take while maintaining the same optimal solution.

Chapter 2 Literature review

2.1 Overview

This review will discuss two relevant streams of literature in relation to the proposed model. The first stream is research related to maximizing the return of care management programs. The second stream is research related to operations research concepts that have been applied in health care that have similarities to the problem at hand.

2.2 Maximizing return on care management programs

While there are successful examples of care management programs generating savings, there are even more examples that have not been so fortunate.³⁴ As many of the Centers for Medicare and Medicaid Services (CMS) demonstration programs have shown, successful programs need to be strategically crafted in order to realize savings.^{8,35} Furthermore, as providers continue taking on financial risk for the patients they care for, the efficiency and need to create a return on investment for these programs has increased. In response to this, there has been an increase in the literature on strategies that maximize return on investment for care management programs in recent years.

^{8,10,14}

In 2013, CHCS published a report that synthesized findings from pioneer programs to date in an effort to raise awareness about best practices. Among the conclusions, they noted that programs were focusing a lot of resources on a few select

patients. In addition to this report, CHCS partnered with the National Governors Association (NGA), the Robert Wood Johnson Foundation (RWJF), and the Atlantic Philanthropies to hold a summit to discuss best practices among super-utilizer programs. Themes from the summit centered around matching patients to the right intervention at the right time. Specifically, they mentioned the use of cluster analysis to identify subgroups of similar patients who would benefit from the same interventions. Among these modeling techniques, they also recognized that the use of a readiness to change factor is an important variable in finding patients who will respond positively to an intervention.¹⁰

CMS also posted an informational bulletin on the subject in 2013. The focus of the bulletin discussed factors that state-level programs should assess when considering implementation of such care management programs. The first suggestion was to start by identifying the group of patients that may be “impactable” among a state’s highest utilizers. Importantly, they suggested identifying super-utilizers as those who have higher than expected utilization given their diseases and condition. This is in contrast to simply identifying the patients who account for the most spending. On the intervention-side, CMS suggested segmenting high ED-utilizers from high inpatient-utilizers as interventions to curtail these costs are likely very different in nature.¹²

Lewis et al., also in 2013, published a report discussing ways to prevent “triple fail” events. They also indicated a strategy to pair patient subpopulations with interventions specifically tailored to that group. In doing so, they called for including a measure of impactability to differentiate similar patients on how likely they are to react

positively to an intervention. Lastly, the creation of a mathematical model to help administrators choose between different interventions and programs to implement was suggested.⁹

In 2014, a Commonwealth Fund report by Hong, Siegel and Ferris specifically summarized their findings on complex care management. Based on 18 successful programs, they identified that key factors in success included identifying patients at risk for poor outcomes, performing comprehensive health assessments, working closely with patients, and being able to rapidly respond to changing conditions. They further recommended a hybrid selection process that utilizes risk prediction, disease criteria, utilization thresholds and provider referrals. Lastly, they noted that intervention protocols, caseloads and location of interactions must be tailored to the intervention group.¹⁷

In 2015, Liaw et. al sifted through the largest CMS care coordination demonstration programs for key insights and best practices based off the few successful demonstrations. Similar to previous reports, they noted that a focus on high-utilizers is critical. On the intervention side, having solutions for mental health treatment and end-of-life care were also determined to be important. Other features they recognized as important were building relationships, access to real-time patient data, and coordinating with primary care practices.⁸ This review was similar to the 2012 report by Brown et. al that summarized key features of the successful programs in Medicare Coordinated Care Demonstrations, but covered more programs.³⁵ To note, Brown's

review was one of the earlier reports that identified the need to more selectively target patients.

Of these best practices, the exact strategies used for patient identification and selection are among those most discussed in detail. In 2013, Haas et al. attempted to determine which predictive model was best for identifying future high-utilizers and those who would have the greatest benefit from a patient-centered medical home setting. They reviewed the performance of several commonly used risk-prediction methods that are based on diagnoses and demographics. Their findings indicated that all the methods performed well relative to each other, with proprietary algorithms producing the best results. Overall, however, none of the algorithms were able to explain more than half of the variability in outcomes. This led them to conclude that including data beyond diagnosis and demographic characteristics may be important in more accurately targeting the right patients.²⁶ One of these additional characteristics that may prove useful is a self-management measure, which indicates how prepared a patient is to take responsibility for their health.³⁶ Arguably, the most commonly used measurement for this is a patient survey called the Patient Activation Measure.

Research has shown that higher levels of activation result in less hospital and emergency department use.^{18,22,23,50} Further support for using such a metric is that research has also shown self-management to be a modifiable characteristic, meaning interventions can be tailored to improve one's self-management.³⁷ Other patient-reported metrics have also shown promise in better predicting health care utilization. Holand et al. (2015) found that patients reporting higher levels of functional

impairment, dependencies and difficulties translated to more costly patients.³⁸ Thus, patient-reported indicators may well provide greater insight into which patients to target.

While there has been a large focus on methods for finding the right patients, less common among the literature are concrete examples of putting all of these best practices concepts to use. Especially sparse are the examples of taking patient selection and matching to the appropriate intervention. Two reports, both published in 2015, discuss actual program approaches and implementations of such programs. The first setting is the Community Care of North Carolina (CCNC), whom takes a population health approach to care management. The second setting setting is at Denver Health (DH), whom the Center for Medicare and Medicaid Innovation (CMMI) gave \$19.8 million to develop the program, which also takes a population health approach.¹¹ Both settings put a focus on finding the patients who are most likely to experience a benefit from an intervention, rather than simply finding high-utilizers. In fact, CCNC indicated that only 53% of their top impactable patients would be classified as high utilizers, indicating that the remaining 47% are high utilizers with low impactability. CCNC has also shown that these impactable patients result in greater savings. One last factor to note is that CCNC considers any patient who has contact with a care manager to have had “care management,” but recognizes that actual interventions vary widely and are tailored to each individual’s needs.¹³

DH, on the other hand, differs in this approach. While they also put a large focus on identifying those impactable patients, they also utilize a tiering system as a way to

match intensity of interventions to the level of care that patients need. In fact, they've made multiple revisions to their selection and tiering algorithms in order to help their care team find and prioritize the patients who benefit most from program interventions. Specifically, their interventions range from passive to high intensity, matched to patients based on need. Low need patients receive electronic interventions such as Short Message Service (SMS) reminders. Patients needing more care are offered care management programs to better manage medications and coordination. Finally, the most complex patients are offered access to high-intensity clinics or ambulatory intensive care units.

In summary, the literature on maximizing return on care management programs is quickly growing and the importance of matching the right patient to the right intervention is a central concept. Furthermore, this concept has been suggested to be used under an administrative lens to identify the most appropriate type of program to implement as well as at a program level in optimizing which patients receive which interventions, among the interventions offered by the program. Finally, actual implementation of these concepts is much less prominent, although a few organizations have identified their success with such strategies.

2.3 Operations research in health care settings

Utilizing operations research techniques in health care has become quite popular in recent decades. Journals such as *Healthcare Management Science*, *Operations Research for Health Care*, and *IIE Transactions in Healthcare Systems Engineering* are

journals dedicated to the application of operations research in health care, all being created in the last 20 years.³⁹⁻⁴² A 2011 survey of operations research usage in health care by Rais and Viana identified key operations research work done in health care, grouped by types of problems or settings. Operations research work that has similarities to this problem fall under the umbrella of resource scheduling and allocation, disease progression, cost-effectiveness and medical decision making.⁴³

Resource scheduling has been used in a variety of settings within health care. Rais and Viana note that nurse scheduling problems have received a considerable amount of attention. This work typically models the optimization of scheduling nurses by meeting their required personnel coverage and also meeting various soft constraints such as personal preference.⁴³ A variant of this, the nurse rostering problem which attempts to find replacement nurses when someone calls in sick, has also been often studied. Bertels and Fahle (2006) sought to minimize home health care costs by considering the transportation to various patients' home. This is particularly noteworthy as many care management programs utilize home-visit component.⁴³ Also noteworthy is the work of Punnakitikashem et al. (2008). They used stochastic programming to solve the problem of assigning nurses to patients in a given shift while considering the differences between a registered nurse and licensed vocational nurse and dividing work into direct care and indirect care, where direct care takes priority over indirect care.^{43,44} This is similar to the care management problem in considering different types of workers and different types of work, however the setting is quite different.

Much of the Resource allocation problems that have been addressed are typically at a macro-level or concern the allocation of supplies and equipment. For example, Flessa (2003) used linear programming models to analyze the optimal allocation of a budget in Tanzania to show how optimal allocation changes for different goals.⁴³ Rauner and Bajmoczy (2003) determined how semi-automated early defibrillators should be distributed to each region in Austria. Van De Klundert et al. (2008) used dynamic programming to optimize the flow of sterile instruments and demonstrated a 20% reduction in savings was possible.⁴²

Some work has been done in allocating resources with respect to medical interventions. However, the goal of these models are typically to maximize health within a budget, rather than considering the possibility of an intervention lowering overall spending. Deo et al. (2013) used a Markov decision process to model the asthma disease states in children. They then coupled this with a scheduling policy to prioritize which patients should be seen each month to maximize quality-adjusted life years (QALYs) for the population. The concept they used to model disease progression and intervention was similar to machine maintenance and repair problems seen in traditional Industrial Engineering.⁴⁵ Earnshaw et al. (2002) used a linear programming model to select sets of interventions to prevent complications of type-2 diabetes. Their model also utilized input of a Markov model to describe disease progression and the objective function attempted to maximize QALYs within budgetary constraints. This research is particularly noteworthy as they consider how patient subgroups will react to different interventions. However, their model focuses only on patients with type-2 diabetes and assesses the

most cost-effective methods for increasing QALYs, rather than considering minimizing overall spending of the system.^{43,46} Maximizing QALYs for a budget has also been considered at a higher level. Chalabi et al. (2008) considered a hypothetical situation that consisted of multiple health care programs, each with multiple treatment options and multiple patient groups. Given these different program-treatment-patient combinations, their model allocated the budget to maximize QALYs, but also considered uncertainty and variability among health outcomes.⁴⁷

The optimization in timing of treatments or use of alternative treatments has also received some attention. On an individual level, the timing of a liver transplant decision and initiation of HIV therapy have been modeled, using disease progression models to solve the problem. Conversely, on a population level, the timing of organ transplants has been modeled.⁴⁵ These models are aimed towards clinical effectiveness. Population-level research on the cost-effectiveness of alternative treatments is also common. With respect to chronic conditions, Paltiel et al. (2006) reviewed an asthma intervention utilizing disease progression modeling and addressing cost-effectiveness.^{43,45} Specifically, Epstein et al. (2007) discussed the long-term financial impact of an early intervention for acute coronary symptom that was shown to reduce mortality rates and improve short-term quality of life. They calculated total health costs for a five-year period after initial intervention. While the early treatment was partially offset by higher costs associated with the conservative treatment in previous years, it still remained the costlier intervention at five years.⁴⁸

Operations research is increasingly becoming more popular in health care. Many of the topics covered to date reflect optimization decisions of traditional acute care settings, such as nurse scheduling and rostering or optimal equipment allocation. However, budgetary allocations and medical-decisions have also been studied to some extent. This research has particularly been in relation to a cost-effectiveness parameter such as cost per QALY. Finally, the modeling of disease progression has been used a component in some of the work, although usually considering a single disease, and not that of a complex patient.

Chapter 3 Problem statement

A lot of attention has been given to care management programs as a way to improve care and reduce spending.^{10,12,17,18,20,30,49,50} The body of literature surrounding the best practices is growing but it is far from being in a mature state.⁸⁻
^{11,13,14,17,22,23,26,51,52} Providers looking to implement care management into their practice can review the current literature to gain an understanding of what types of strategies tend to be successful, but there is still a lot of trial and error required among each individual program. As public and private payers are continuing their move towards alternative, value-based, payment models, providers are facing increasing pressure not only to quickly adopt care management programs but also to ensure they are cost-effective.³

As indicated in the literature, in order to provide efficient and effective care management, the decisions of which patients receive care management, coupled with the type and amount of care management they receive, need to be carefully chosen.⁸⁻
^{11,13,14,17,22,23,26,51,52} Naturally, the ramifications of these decisions are further extrapolated in environments where there are not enough resources to interact with all patients. In operations research, this type of optimization problem is generally known as a resource allocation problem and is commonly solved with linear or mixed-integer programming.

In order to address this problem, the data and information from the LIGHT2 project was analyzed. Based on this analysis, a mixed-integer programming model is

formulated to maximize a care management program's resources in a population health setting. Building on patient segmentation and patient-tailored interventions that are discussed in the literature, the model seeks to pair segments of patients with the intervention protocol that is best fit for them.^{3,4,6,11,14-17} Furthermore, the model identifies which patients will be reached to minimize overall spending, given a program's resource limitations.

This model is a conceptual model that was developed based on what LIGHT2 provided and discussions with the health care members of the LIGHT2 team. The objective of the model is to provide a baseline model that can be modified to address whatever scenario may arise in a health care setting. The testing of the model will be important but at the moment with the lack of relevant data it is not possible to test the model. We can though, assess it conceptually, in terms of modeling the problem and the needs of the problem.

Chapter 4 Model formulation

4.1 Problem description

4.1.1 Setting and background

The model created is specifically tailored to a setting that utilizes a care management team with the goal being to minimize the overall spending required to properly care for the population. While not all care management plans fit this criteria, we focused our attention to this setting for three reasons. First, with the rise in popularity of ACOs, it seemed appropriate to tailor the model to a setting that matches an ACO's use case. Secondly, the two programs described in the literature, Denver Health and Community Care of North Carolina both employ population health strategies. Thirdly, this setting allowed us to keep a rather simple model while effectively describing the situation.

The model also presumes there are three types of workers on the care management team: physicians, nurses, and social workers. Furthermore, it presumes that physicians can also perform some of the work of a nurse or social worker. Similarly, a nurse is presumed to be able to perform some of the work of a social worker. In reality, each individual care management program is likely to have a unique set of workers on their team. We choose to model this three-tier worker hierarchy as a proof of concept that the model can account for different team members and the ability for some team members to perform the work of others on the team, if needed.

4.1.2 Patient cohorts

The model also assumes there are different patient cohorts or subpopulations within the population. Again, this is current with the literature on best practices. Technically, the model is indifferent to how patient cohorts are selected. However, as Lewis et al. indicated, the goal of segmenting, or clustering in data analytics, is to create subgroups that are homogenous among the individual's belonging to the subgroup but heterogeneous from other subgroups.⁹ Furthermore, the similarities among groups should be such that interventions would be equally effective among all members of the group. Thus, simply grouping patients by amount of health care spending, for example, would not be a good strategy, as there may be very different interventions needed to bring specific individuals under control. Based on the literature, it is recommended that medical, behavioral and social factors all be considered in patient clustering analyses as a data preparation step.^{9,25,26,36,37,53}

4.1.3 Intervention protocols

The other component to the model are the interventions used. In the model, the interventions are mutually exclusive of each other; only one intervention can be applied to each patient. Based on this modeling concept, the interventions input into the model can be thought of as alternative protocols that patients could be administered. For example, one protocol may include self-management coaching, medication management and a home visit. Another protocol may include self-management coaching, medication management, but provide housing assistance rather than a home

visit. The reason for having the model pick one exclusive protocol is due to the complexity that would be needed for the model to determine the right combination and intensity of intervention options. Both aspects, combining interventions and choosing the intensity, are likely to be nonlinear in nature and would also require large amounts of data to be accurate as the relationship between effectiveness and intensity would need to be modeled at different levels for each patient cohort. Furthermore, the concept of protocols is easy to understand and implement.

4.1.4 Cost metric

Once patient cohorts and intervention protocols are decided, the model will need information pertaining to the costs of administering a protocol and the expected savings (or loss) of the protocol. These values are needed for each specific patient cohort the intervention protocol may be given to. There are multiple ways one could gather this data. The first aspect, the cost of administering a protocol, could be measured based on historical data or estimated based on literature and subject matter expert judgement. One item to note about the cost of administering an intervention is that the cost likely varies between patient subgroups. For example, the amount of time required to perform medication management likely depends on how many chronic conditions a person deals with and which chronic conditions those are. The second aspect, savings expected from a protocol given to a specific population could similarly be determined by either historical data or literature and subject matter expert

judgement. Again, historical data would be preferred, but may not be available depending on where a group is in their implementation of a care management program.

4.2 Model formulation

4.2.1 Notation

For the model, the i, j, k indices will be used to denote the following items:

i = Patient cohort or subpopulation i

j = Intervention set j

k = Type of worker k

4.2.2 Data parameters

Data parameters are the input data that are needed in order to run the model.

The parameters are listed here:

P_i = Total number of patients in each patient cohort or subpopulation i

S_{ij} = Expected savings yielded from administering intervention set j to a patient in segment i

T_{ijk} = Amount of worker-type k 's time used to administer intervention set j to a patient in segment i

R_k = Total number of available hours per year per worker-type k

E_k = Total number of worker-type k 's available

C_k = Cost per hour of an worker-type k

BC_i = Baseline costs per patient in cohort i (current spending without intervention)

4.2.3 Decision variables

Decision variables are the components of the model that the program can adjust in order to optimize the objective function. As discussed, the decision to be made is which patients should receive which interventions. Consequently, to account for the possibility of there only being a few cost-savings opportunities, the amount of resources allocated is also a decision variable. We are also allowing for workers to do other types of work, meaning that the actual type of worker that performs the activity for an intervention is also a decision variable. This will be explained further in the constraints section, but this is why the $Y_{kk'}$ decision variable is needed. The decision variables are formally described in the model as:

X_{ij} = Number of patients in cohort i that are administered intervention protocol j

H_k = Total number of hours used by worker-type k

Z_k = Total number of worker-type k hours demanded to administer chosen protocol

$Y_{kk'}$ = Number of worker-type k hours spent performing worker-type k' work

The first decision variable, X_{ij} , can be viewed as the primary decision variable. The variable describes which patients receive which interventions. The latter three decision variables listed are used to allocate the cost of the interventions being performed. As discussed, multiple variables are needed because the model allows for the possibility of some workers to perform the work of others. Essentially, these

variables work together to determine the most cost effective resources to use. This will be further explained in the constraints section.

4.2.4 Objective function

The objective function in the model seeks to minimize overall spending. This is done with three terms. The model starts with the estimated baseline spending required to manage the population without any care management interventions. Then, the model adjusts the spending needed by adding the cost required to administer interventions and subtracting the estimated savings from the interventions. The full objective function is listed below:

$$\text{Minimize } \sum_k [C_k * H_k] - \sum_i \sum_j [S_{ij} * X_{ij}] + \sum_i [BC_i * P_i] \quad (4.1)$$

Broken down into the three components, we see the first component calculates the spending required to administer interventions. This is calculated as the number of hours required for a worker multiplied by the cost per hour of a worker. Since there may be multiple types of workers, each worker-type is calculated separately and summed. Recall that H_k is a decision variable for the number of worker-type k hours used. Thus, this value fluctuates as the decision variables change. The first component is shown in isolation below:

$$\sum_k [C_k * H_k]$$

The second component computes the savings for administered protocols. The savings per patient for a protocol administered is multiplied by the number of patients

given that protocol in a patient cohort. As the amount of savings differ across patient cohorts, the savings for each of the patients receiving an intervention are summed. Again, recall that X_{ij} is a decision variable relating to the number of patients in a cohort receiving a certain intervention protocol. Thus, as the variables change, so will the objective function. The savings component is shown in isolation below:

$$\sum_i \sum_j [S_{ij} * X_{ij}]$$

The third component is the baseline spending. This is the current spending required for each patient segment, multiplied by the amount of patients in the segment. Notice that this term does not contain any decision variables; only constants are present. As such, this term will not change as the decision variables change. In fact, the model will find the same solution if this term is omitted. However, we choose to keep the term so that the solution value is the total spending expected, not just the total difference the interventions have on the system. The baseline spending component is shown in isolation below:

$$\sum_i [BC_i * P_i]$$

4.2.5 Constraints

The constraints in the problem define the range of values the decision variables can take so that the problem determines a feasible solution to the real world problem.

The constraints for the problem are shown below:

$$\sum_i \sum_j [T_{ijk} * X_{ij}] \leq Z_k \quad \forall k \quad (4.2)$$

$$\begin{aligned} Z_1 &\leq Y_{11} \\ Z_2 &\leq Y_{12} + Y_{21} \\ Z_3 &\leq Y_{13} + Y_{22} + Y_{31} \end{aligned} \quad (4.3)$$

$$\begin{aligned} H_1 &\geq Y_{11} + Y_{12} + Y_{13} \\ H_2 &\geq Y_{21} + Y_{22} \\ H_3 &\geq Y_{31} \end{aligned} \quad (4.4)$$

$$H_k \leq R_k * E_k \quad \forall k \quad (4.5)$$

$$\sum_j X_{ij} \leq P_i \quad \forall i \quad (4.6)$$

$$\begin{aligned} 0 &\leq X_{ij}, \text{ integer } \forall (i, j) \\ 0 &\leq H_k, Z_k \quad \forall k \\ 0 &\leq Y_{kk'} \quad \forall k \end{aligned} \quad (4.7)$$

The first four constraints (4.2, 4.3, 4.4, 4.5) work together to ensure the care team has the resources to cover all the intervention protocols that the model assigns to patients. The left-hand side of the first constraint (4.2) calculates the number of hours of each worker-type that is needed to administer the interventions that have been assigned. Z_k must be able to be as large as this value in order to ensure there is enough resources to perform all the assigned protocols. The second set of constraints (4.3) allows for flexibility among which resources perform which tasks. For example, the first equation in the set shows that only the physician ($k = 1$) can perform the physician's work. Conversely, the physician is able to perform the work of the nurse (denoted as Y_{12}) or the social worker (denoted as Y_{13}). While this may not seem like an efficient practice, as the higher-level workers are a more expensive resource, in an environment with fixed resources it may be optimal in order to fully utilize the resources currently available. For example, having the physician do work that could be done by a nurse is

preferable to the physician being idle. The third set of constraints (4.4) calculates the number of hours each worker type spent by adding the $Y_{kk'}$ to account for any time spent covering other types of work. Finally, the fourth constraint (4.5) ensures that the total working hours for each worker type is less than or equal to the total amount of available hours available for that type of worker. The fifth constraint (4.6) ensures that each patient can only receive one intervention set. Without this constraint, the model would essentially choose the largest cost-to-savings margin that existed among the options and allocate all the resources to administering the one intervention set to the one patient cohort. The last constraint set (4.7) ensures non-negativity for the decision variables. This is a necessity so that the model does not assign a negative amount of interventions that are cost ineffective and ensure that, similarly, a negative amount of hours are not assigned.

4.2.6 Complete formulation

The complete model formulation is shown below:

$$\text{Minimize } \sum_k [C_k * H_k] - \sum_i \sum_j [S_{ij} * X_{ij}] + \sum_i [BC_i * P_i] \quad (4.1)$$

Subject to:

$$\sum_i \sum_j [T_{ijk} * X_{ij}] \leq Z_k \quad \forall k \quad (4.2)$$

$$\begin{aligned} Z_1 &\leq Y_{11} \\ Z_2 &\leq Y_{12} + Y_{21} \\ Z_3 &\leq Y_{13} + Y_{22} + Y_{31} \end{aligned} \quad (4.3)$$

$$\begin{aligned} H_1 &\geq Y_{11} + Y_{12} + Y_{13} \\ H_2 &\geq Y_{21} + Y_{22} \\ H_3 &\geq Y_{31} \end{aligned} \quad (4.4)$$

$$H_k \leq R_k * E_k \quad \forall k \quad (4.5)$$

$$\sum_j X_{ij} \leq P_i \quad \forall i \quad (4.6)$$

$$\begin{aligned} 0 &\leq X_{ij}, \text{ integer } \forall (i, j) \\ 0 &\leq H_k, Z_k \quad \forall k \\ 0 &\leq Y_{kk'} \quad \forall k \end{aligned} \quad (4.7)$$

4.2.7 Assumptions and limitations

The model shown has a few assumptions and limitations that have not yet been specifically addressed. These items are described below:

- Assumption 1:** The model assumes each patient in a patient cohort will react similarly to each possible protocol. This assumption is fairly strong as long as the patient cohort process goes beyond grouping patients simply by chronic conditions and utilization. Research has shown behavioral and social factors also influence receptivity of interventions among patients. Furthermore, if variations in effectiveness are shown within cohorts, this should be a flag to further analyze the make-up of the patient cohorts.
- Assumption 2:** The goal is to minimize overall spending. In the model presented, there is no consideration of quality, only spending. Thus, the assumption is that care that is less expensive, such as outpatient visits and follow-up check-ins, will be higher quality care as well. Further underlying this assumption is the concept that the goal is to manage long-term population health. As such, higher quality care should be related to savings from the current baseline.
- Assumption 3:** lower-level work can also be performed by higher-level workers. In the model presented, we offered three tiers of workers and allowed higher

tiers (such as physicians) the ability to perform some of the lower tier work (such as a nurses and social workers). In real care teams, this may or may not be applicable. With slight tweaks to the constraints, the exact cross-work scenarios could be modeled.

- **Limitation 1:** Patient deaths are not considered. This is similar to the first assumption, as it relates to the concept of quality. An intervention that actually increased mortality rates could show up as reduced spending, depending on how the cost and savings metrics were defined. It is recommended that this is assessed in the data cleaning stage of preparing the input data.
- **Limitation 2:** The availability of accurate input data. As with any model, the accuracy and value of a model is only as good as the input data. As such, it's unknown how much data exists on how costly specific interventions are and how cost-savings they are. This is largely due to the heterogeneous format of the literature thus far on performance of care management programs. Even if extremely robust data is not available, the model is still valuable to analyze various what-if scenarios and better understand how changes effect the system as a whole.

4.3 Applying the model: LIGHT2

4.3.1 Overview

One of the limitations of the model, of any model, is having the right data to input. Given the nascent state of care management, especially among programs

incorporating information technology effectively, having the necessary data for the model may prove to be an obstacle. As described earlier, one program that has incorporated technology into their care management program is the University of Missouri Health Care. Their LIGHT2 program was funded by CMS to leverage information technology in a care coordination program. From July 1st 2013 to July 1st 2015, the Nurse Care Managers (NCM) documented their time and activities into a care management system as part of the program. The program took a population management approach by enrolling all Medicare, Medicaid, and dual-eligible patients from the hospital's primary care clinic and utilizing a four-tier system based on number of chronic conditions and health care utilization to prioritize work and identify a specific protocol for each tier. Similar to Denver Health, the tiering system provided a way to match the right patient to the right intervention and help NCMs prioritize where they should focus their attention.

Intentionally, the protocol developed for each tier was meant to be only a guideline for the minimum amount of care provided. This allowed the NCMs flexibility to tailor their efforts to the patients that needed it most. Popejoy et al. reviewed the data recorded in the documentation system to analyze how well the protocol was followed and what nurse care managers spent their time on. They noticed that while the care managers largely adhered to the protocol guidelines, about 65% of the patients in tier 2, a tier not requiring care management defined by the protocol, also received some level of care management.³⁰

Given the unique and high-tech characteristics of the LIGHT2 program's flexible protocols that were given to a wide range of patients with care managers documenting their activity, the program is a good candidate to apply this model to. This is because LIGHT2 now has a plethora of patient and intervention data over a two-year program period. A model specific to the LIGHT2 program is outlined next, and the limitation of input data is specifically addressed.

4.3.2 LIGHT2 Model

To apply the model to the LIGHT2 program, the program's characteristics need to be reviewed to ensure the model accurately depicts the program. The biggest factor in this assessment is the make-up of the care management team. The model presented considered a team that consisted of three different types of workers: physicians, nurses, and social workers. Furthermore, it was assumed that cross-work could occur where a physician could do the work of a nurse or a social worker and, similarly, a nurse could also do the work of a social worker.

The LIGHT2 program utilizes only one worker-type, the NCM, who provided all aspects of care management. Of course, the NCM consulted other medical professionals as part of their work, however, these aspects are considered as an activity the NCM did, rather than an additional team member of the care management program. Only having one type of worker allows the model to be simplified, as the constraints required for allowing cross-work can be removed. Furthermore, index k , the number of employee-

types in the model, is set to 1. Below is the LIGHT2-specific model with this simplification:

$$\text{Minimize } [C_1 * H_1] - \sum_i \sum_j [S_{ij} * X_{ij}] + \sum_i [BC_i * P_i]$$

Subject to:

$$\sum_i \sum_j [T_{ij1} * X_{ij}] \leq H_1$$

$$H_1 \leq R_1 * E_1$$

$$\sum_j X_{ij} \leq P_i \quad \forall i$$

$$0 \leq X_{ij}, \text{ integer } \forall (i, j)$$

$$0 \leq H_1$$

Having the model identified, we can now address how the input data can be generated.

4.3.3 Defining Baseline Costs and Cost-Savings (Loss) per Patient

The first component of the input data to address is the measurement of baseline cost and cost-savings. Again, a program's goals and data-availability will drive what metrics are possible for use. As a starting point, the cost metric used for LIGHT2 can be a simple pre-post intervention comparison, calculating the difference in spending a patient required for the one year before the program with the spending the patient required in the one year after the program started. Thus, each patient will have a

baseline cost and a cost-savings (loss) calculated. This will be used later at the cohort-level.

To note, a full conversation can be had on better addressing this decision. For example, a more rigorous approach may be to utilize propensity score matching to define a similar cohort of Medicare and Medicaid patients that did not receive any care coordination. Doing so would help protect the model against regression-to-the-mean and time-series effects that may influence the results. Similarly, arguments could be made about adjusting the one-year time frame. Nonetheless, once the cost metric is decided, the baseline cost and net cost effect can be calculated for each patient.

4.3.4 Defining Patient Cohorts, $i = 1, 2, 3, \dots, n$

The second component of the input data is classifying each patient into a patient cohort. The cohorts created are the i index and cohorts can be arbitrarily labeled from 1 to n , depending on the number of cohorts. Cohorts can be defined by means of a clustering analysis. As discussed, the intention of cohorts is to group similar patients to the extent that all patients in one group will react similarly to interventions. As such, including behavioral and social factors, along with medical factors, is recommended when performing the clustering analysis. Along with considering which factors to include in a clustering analysis, the number of clusters, or patient cohorts, also needs to be decided. The key in this decision is to balance the level of homogeneity within each group with the balance of available data. In order for the model to identify which intervention is most effective to each patient cohort, there must be sufficient data

available to assess different interventions that were given to each cohort. Thus, choosing too many clusters may result in too little of intervention data for each cluster. For LIGHT2, a lower-bound would be four segments, as that is what was used in the tiering system. However, because there was a large variance of care management intensity noticed within tiers, more cohorts should be utilized. Finding the right number of segments may be an iterative process involving clustering analysis, review of intervention data available per cluster, and clinician feedback.

Given these considerations, the below table is an example of patient-variables that could be used in the clustering analysis:

Variable	Type	Definition
Gender	Categorical: male, female	Listed gender
Age	Continuous.	Age at start of program
Insurance type	Categorical: Medicare, Medicaid, Dual	Insurance at start of program
# of chronic conditions	Categorical: 0, 1, 2, 3, 4, 5+	Count of the 19 chronic conditions listed by CMS present at start of program
Mental health disease	Categorical: yes, no	Presence of one or more mental health diagnosis codes on medical history at start of program
Obesity	Categorical: yes, no	BMI > 30 at start of program
Area Deprivation Index	Continuous.	Index of socioeconomic deprivation based on patients home address

Table 1: Patient variables for clustering analysis of patient cohorts

Note that no consideration is given to past utilization. Depending on how well the clustering analysis actually performs, it may be appropriate to add this factor. However, adding utilization may wrongly group patients together based on utilization characteristics, even though they may be very different patients in terms of medical, behavioral, and social characteristics. Thus, by excluding utilization, the cluster will group patients simply on patient-centered characteristics.

4.3.5 Defining Intervention Protocols, $j = 1, 2, 3, \dots, m$

Similar to the creation of patient cohorts, the intervention protocols need to be defined. The protocols can be arbitrarily labeled from 1 to m , depending on the number of protocols. LIGHT2 can use a clustering analysis to identify the different intervention protocols that NCMs gave to patients. Since the LIGHT2 tiering protocols were based on a one-year time period, it is suggested to utilize this timeframe when identifying protocols. Each of the domains that NCMs could log time in should be a variable with the value of the variable being the number of touches recorded. An additional variable, total touches, can also be included to give an indication of overall intensity. These variables are listed in the table below:

Variable	Type	Definition
Total touches	Continuous	Total number of touches in first year
Communication	Continuous	number of touches in domain in first year
Assess needs and goals	Continuous	number of touches in domain in first year
Facilitate transition	Continuous	number of touches in domain in first year
Self-management support	Continuous	number of touches in domain in first year
Change response/monitor event	Continuous	number of touches in domain in first year
Negotiate responsibility	Continuous	number of touches in domain in first year
Plan of care	Continuous	number of touches in domain in first year
Align resources and needs	Continuous	number of touches in domain in first year
Community resources	Continuous	number of touches in domain in first year

Table 2: Variables for intervention protocol clustering analysis

Note that the clustering analysis is based on touches, rather than time. Touches are used as they are more applicable to a protocol. A protocol may indicate that “assess needs and goals should be performed twice a year.” This is a more straightforward approach compared to a time-based approach such as “assess needs and goals should be performed for 15 minutes a year.” Under the latter direction, it’s unclear how often this topic should be addressed with the patient. However, as the time per touch is likely to be different per patient cohort, we will calculate the cost of intervention for each patient cohort based on the time per touch specific to each patient cohort.

4.3.6 Calculating T_{ij1} and S_{ij} values for patient-protocol combinations

At this point in the data preparation process, each patient in the analysis belongs to a patient cohort (i) and an intervention protocol (j), has a calculated savings (loss) based on their pre-post utilization difference, and has a baseline cost associated with them. This data is now used to calculate the average savings (or loss) (S_{ij}) and intervention time (T_{ij1}) of each intervention protocol for each patient cohort. The result will be two data matrices, such as the following two tables:

	Protocol 1	Protocol 2	Protocol 3
Patient cohort 1	S_{11}	S_{12}	S_{13}
Patient cohort 2	S_{21}	S_{22}	S_{23}
Patient cohort 3	S_{31}	S_{32}	S_{33}

Table 3: patient-protocol savings matrix

	Protocol 1	Protocol 2	Protocol 3
Patient cohort 1	T_{111}	T_{121}	T_{131}
Patient cohort 2	T_{211}	T_{221}	T_{231}
Patient cohort 3	T_{311}	T_{321}	T_{331}

Table 4: patient-protocol time to administer (NCM time) matrix

These tables are created by taking the average intervention time associated with all the patients in a cohort that received a given protocol. For example, if ten patients in patient cohort 1 are assigned to protocol 1, the average time NCMs spent with these patients over the year would be used to create T_{11} and the average of the savings for these patients would create S_{11} . It's likely that not all the patient cohorts will have patients who received each protocol. When this is the case, the savings parameter can be given an arbitrarily large negative value. This will ensure that the model does not choose to administer this intervention. The time parameter can take a value of zero as the savings parameter is sufficient to ensure this combination is not used. For cases where the amount of patients given a certain intervention protocol is very small, the same technique can be applied to ensure the cohort-protocol combination is not chosen.

4.3.7 Remaining data parameters

Having tailored the model to the specific LIGHT2 care management setting and addressed the data preparation steps for the time and savings parameters, the remaining input data are easily available:

P_i : Number of patients in each patient cohort. Calculated by counting the number of patients in each cohort.

R_1 : Number of available hours per year per NCM. This value can be determined based on knowledge of NCM scheduling practices or by averaging the amount of time NCMs accumulated in the documentation system.

E_1 : Number of NCMs on the care management team.

C_1 : Cost per hour of one NCM. This value can be derived by taking the average compensation value (salary plus benefits) for the NCMs divided by the number of available hours an NCM has per year.

4.3.8 LIGHT2 Model Comments

The LIGHT2 model shown above is one example of how data could be prepared to be input into the model presented. The example is possible because of the unique situation created at LIGHT2 where NCMs were given freedom to go above the minimum protocol to deliver the care they deemed necessary to patients. As such, different intervention “protocols” were naturally given to different patients as a result of 25 NCMs all working slightly differently. Thus, the model will be selecting the best of the options that were administered by LIGHT2 NCMs to LIGHT2 patients. This is valuable because knowing that the recommendations have been tried with LIGHT2 NCMs and LIGHT2 patients creates more confidence that making changes will translate into positive results.

Conversely, that is also a limitation of this specific strategy. The model can only choose from the interventions that are input, so we are assuming the protocols administered by the NCMs are the best options available. While this is a likely a good assumption as nurses are usually very well in-tuned with their patients, it doesn't allow for consideration of new interventions that the NCMs weren't able to test.

Nonetheless, this analysis is a very valuable next step for the care management program at the University of Missouri Health Care. They will be able to consider refinement of tiers based on the model's recommendations. For example, the model should get closer to identifying those 65% of tier 2 patients that were given care management, if the efforts applied to these patients was able to move the cost needle. This could further result in helping the NCMs find these patients who need care easier, and ensure they are providing the right type of work at the right intensity.

Chapter 5 Conclusion and future research

5.1 Conclusion

A mixed-integer programming model was presented that can be used to identify the optimal allocation of care management resources through matching of patient subgroups to intervention protocols. While the concept and model is simple and fairly intuitive, the difficulty may lie in the ability to input good data. Nonetheless, the model can serve as a valuable decision-making tool for both clinic administrators interested in gaining insights into the effectiveness of implementing a care management program and program designers looking to optimize their allocation of resources.

5.2 Future research

This paper addresses the need in the literature for a mathematical way to model patient-intervention selection. Specifically, it follows the future research suggested by Lewis et al. who detailed the steps involved in matching patients to interventions.⁹ It also builds on the impactability concept seen in the literature and in practice.^{10,13,24,25} To date, most applications of impactability have largely been geared solely at the patient selection portion of a program design, and whether or not a patient will be impacted by enrollment into a care management program. The model presented builds onto that idea by allowing for multiple intervention protocols to be considered and thus impactability must be considered for each intervention protocol offered. To our

knowledge, this is the first attempt at optimizing the effectiveness of multiple aspects of a care management program through a mathematical model.

There are a many exciting avenues for future research on this subject. First off, this model optimized a fixed set of resources. A future model could remove this constraint and attempt to find the optimal amount of resources and caseload. Another aspect would be to expand the vantage point of the model beyond the care management program. As the overarching goal is to provide quality care at the lowest costs, expanding the viewpoint to include more parts of the system may produce a more holistic and accurate picture of the system at large. This model operates on the assumption that lower costs also produce quality care. A follow-up model could add constraints that enforce quality care per some standard. Alternatively, there are also some interventions that may not be cost-savings, but due to the increased quality of care, they are worth pursuing. These items would also not be recognized in the current model, but a quality goal could be built into the objective function in an attempt to capture these opportunities. As mentioned in the paper, one could also pursue a model to optimize the protocol by letting the model decide which interventions to combine and how much intensity of each intervention to apply. Lastly, for programs already using a tiered or multi-protocol approach, an independent analysis could be done with this model and then compared to the current tier system as a way to refine performance.

In addition, it would also be advantageous to look at the model in terms of the probabilities of the interventions having an impact and the impact of interventions on movement from one tier to another. This would involve possibly developing a Markov

decision process or a stochastic process. With the right data it might also be possible to develop a simulation model to give more insight into the impact of care management and NCMs. This appears to be an area ripe for more analytic methods to assess how care can be provided so as to give better outcomes.

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