Reducing Avoidable Admissions Through the Emergency Department at Massachusetts General Hospital

by

Jordan S. Hoffmann

B.S., Engineering Management, United States Military Academy at West Point, 2004

Submitted to the MIT Sloan School of Management and the Department of Mechanical Engineering in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration

and

Master of Science in Mechanical Engineering

in conjunction with the Leaders for Global Operations (LGO) Program at the
MASSACHUSETTS INTITUTE OF TECHNOLOGY
June 2017

Author ____ Signature redacted
MIT Sloan School of Management and the Department of Mechanical Engineering
May 12, 2017

Certified by ____ Signature redacted
Retsef Levi, Thesis Advisor
J. Spencer Standish (1945) Professor of Operations Management

Certified by ____ Signature redacted
Duane Boning, Thesis Advisor
Clarence J. LeBel Professor, Electrical Engineering and Computer Science

Certified by ____ Signature redacted
Stan Gershwin, Thesis Reader
Senior Research Scientist, Department of Mechanical Engineering

Accepted by ____ Signature redacted
Rohan Abeyaratne
Chairman, Committee on Graduate Students, Department of Mechanical Engineering

Accepted by ____ Signature redacted
Maura Herson
Director, MBA Program, MIT Sloan School of Management

Reducing Avoidable Admissions Through the Emergency Department at Massachusetts General Hospital

by

Jordan S. Hoffmann

Submitted to the MIT Sloan School of Management and the Department of Mechanical Engineering on May 12, 2017, in partial fulfillment of the requirements for the degrees of

Master of Business Administration

and

Master of Science in Mechanical Engineering

Abstract

Despite efforts to address capacity constraints with a massive expansion less than five years ago, the Emergency Department (ED) at Massachusetts General Hospital (MGH) is again displaying consistent and serious symptoms of overcrowding, including rising patient wait times and routine activation of capacity-related emergency management protocols. As MGH grapples with these challenges, it is imperative to understand precisely what is driving the congestion. In this thesis, we: i) show there has been significant volume growth, and ii) study whether these visits resulted in inpatient admissions that could have utilized alternative care pathways while preserving patient safety and quality of care.

After collaborating with hospital staff to analyze ED patient volume in 2015, we conclude that avoidable admission candidates who transferred to MGH from other facilities occupied nearly 6 percent of the hospital's General Medicine capacity. Furthermore, the utilization growth associated with these patients was equivalent to 1.3 percent of all General Medicine beds, meaning transfers alone can account for the overcrowding symptoms mentioned above. In a second analysis, applying unsupervised and supervised learning methods to short-stay inpatients reveals that even generalized order data can reliably predict conditions associated with avoidable admissions. Building on this insight, we then develop a scoring method to identify avoidable admission candidates without requiring manual case review by a physician.

Thesis Advisor: Retsef Levi
Title: J. Spencer Standish (1945) Professor of Operations Management
MIT Sloan School of Management

Thesis Advisor: Duane Boning
Title: Clarence J. LeBel Professor, Department of Electrical Engineering and Computer Science

Thesis Reader: Stan Gershwin
Title: Senior Research Scientist, Department of Mechanical Engineering

This page intentionally left blank

The author wishes to acknowledge the Leaders for Global Operations Program for its support of this work.

This page intentionally left blank

Acknowledgments

This thesis would not have been possible without the generous support of many people. Professors Retsef Levi and Duane Boning, thank you for the invaluable guidance you provided throughout the research process and the thoughtful edits you made to this document. It was a privilege to have each of you as an advisor. Dr. Peter Dunn, Bethany Daily, and Cecilia Zenteno, thank you for your enthusiastic support of the MGH-MIT collaboration and your obvious commitment to improving healthcare operations at MGH.

Kimia Ghobadi, I cannot thank you enough for the steadfast technical and moral support you provided over the past 15 months. Your empathy, flexibility, and patience were all truly appreciated. John Silberholz, your assistance with the coding and data science aspects of this project was crucial. Thank you for going above and beyond what you initially agreed to do. Liz Ugarph and Mariam Al Meer, I am so fortunate to have shared this experience with you as fellow interns. Thank you both for being so supportive and fun to work with.

A special thank you to the members of Capacity Task Force 1. I have honestly never met a more caring, competent, and professional group of people. Doctors Ali Raja, Luis Tacona, and Brian Yun, thank you for providing the clinical perspectives critical to ensuring the validity of the analysis. Thank you also to the many attending physicians, nurse practitioners, and nurses at MGH who allowed me to shadow them as they performed their work. Your professionalism and commitment to patient care was truly inspiring.

Finally, I want to thank my incredible family. To my parents, Al and Jill, and my brother, Adam, thank you for all your love and support. To my children, Clara, Evie, and Grey, thank you for being such wonderful sources of joy and inspiration. Of anything I have accomplished, I am most proud to be your dad. Above all, thank you to my beautiful wife, Krista, who shouldered an incredible burden while I focused on completing the LGO Program. Our kids could not ask for a better mother, nor I for a better partner.

Contents

List of Figures

This page intentionally left blank

List of Tables

This page intentionally left blank

Appendices

This page intentionally left blank

Chapter 1

Introduction

This chapter provides an overview of the hospital and department hosting the study, the motivation and hypotheses guiding the work, key findings, and the general organization of the remainder of the document.

1.1 Massachusetts General Hospital

Founded in 1811, Massachusetts General Hospital (MGH) is the oldest and largest hospital in New England.[1] It is widely regarded as one of the leading healthcare institutions in the United States and is consistently ranked as one of the top hospitals in the nation by *U.S. News & World Report*. According to the *U.S. News* survey, MGH has ranked among the top three hospitals in America 18 of the last 25 years, including when it received top honors in both 2012 and 2015.[2] Further underscoring the hospital's commitment to excellence, MGH has been designated a Magnet hospital by the American Nurses Credentialing Center (ANCC) since 2003. Awarded to less than seven percent of all U.S. hospitals, Magnet recognition is considered the gold standard in professional nursing practice.[3]

Beyond delivering world-class patient care, MGH also performs groundbreaking medical research that has led to several revolutionary surgical innovations, including the use of general anesthesia and telemedicine.[4] Today, it conducts the largest hospital-based research program in the United States and is the top recipient of research funding from the National Institutes of Health (NIH). In total, the hospital boasts an annual research budget of more than $800 million.[1]

Located in the West End neighborhood of Boston, MGH serves as the original and largest teaching hospital of Harvard Medical School (HMS), as well as a tertiary[i] referral center for complex patients from around the world.[5] Each year, the 999-bed medical center admits approximately 48,000 inpatients, records more than 100,000 emergency room visits, handles nearly 1.5 million outpatient visits, and performs over 42,000 operations. With over 23,000 employees, MGH is the largest nongovernment employer in Boston.[1]

In 1994, MGH affiliated with Brigham and Women's Hospital to form Partners HealthCare, an integrated healthcare delivery system that includes community hospitals, primary care and specialty physicians, community health centers, and other health-related entities. Over the past two decades, Partners has expanded to include several other hospitals, including North Shore Medical Center, Newton-Wellesley Hospital, and Faulkner Hospital, making it the largest healthcare provider in Massachusetts.[6]

---

[i] In the medical field, *tertiary* refers to highly-specialized medical care, usually over an extended period, that involves advanced and complex procedures and treatments performed by medical specialists in state-of-the-art facilities.[18]

1.2 MGH-MIT Collaboration

The MGH-MIT Collaboration is a long-standing research partnership between MGH and the Massachusetts Institute of Technology (MIT) Sloan School of Management. The partnership aims to improve quality of care and reduce costs by applying operations research and continuous improvement methodologies to the hospital's most pressing operational challenges. Incorporating both clinical and research expertise, the Collaboration consists of leaders from MGH, faculty from MIT, postdoctoral fellows from the Operations Management group at the Sloan School, students from the MIT Leaders for Global Operations (LGO) Program, and others.

Established over a decade ago, the Collaboration originally focused on driving improvements exclusively within the hospital's Perioperative Department, with projects focused on optimizing inpatient flow,[7] [8] [9] operating room block allocation,[10] and surgical inventory management.[11] More recently, the Collaboration has expanded its scope to include other departments and functions within MGH, including primary care prescription management,[12] infusion clinic appointment scheduling,[13] [14] and just-in-time bed assignment in the Neurosciences ICU.[15] The effort presented in this document, and performed within the framework of an IRB-approved study, marks the Collaboration's first project focused solely within the hospital's Department of Emergency Medicine.

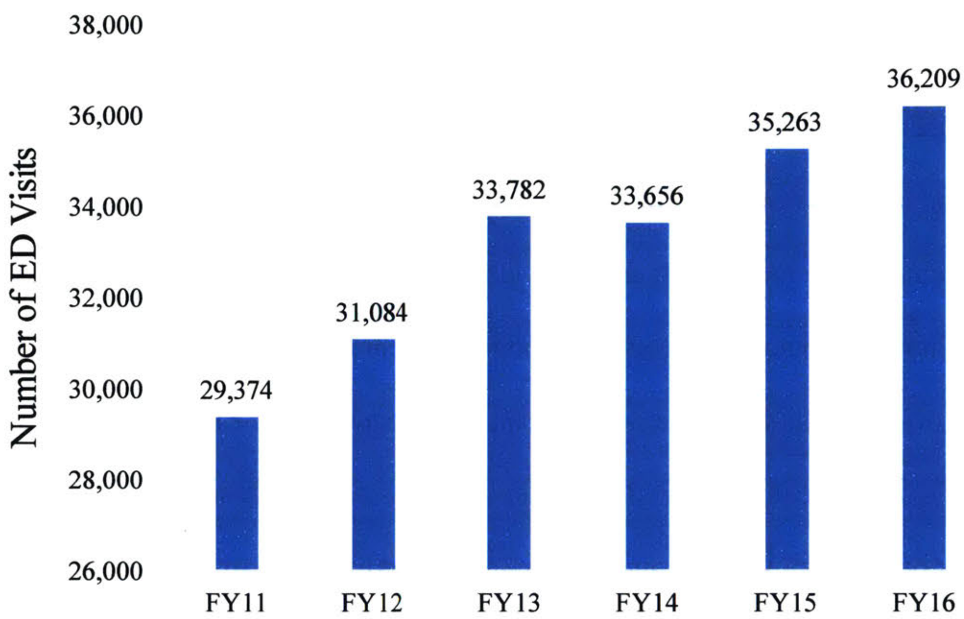
1.3 The Emergency Department (ED)

The Sumner M. Redstone Emergency Department (ED) specializes in acute care for patients arriving to MGH without prior appointment, either by their own means or by that of ambulance or medical helicopter.[16] Due to the unplanned nature of these visits, the department must assess and treat a broad spectrum of illnesses and injuries, including many that are life-threatening and require immediate medical intervention. The beneficiary of a $500 million expansion and renovation that concluded in 2014,[16] today the ED constitutes a full-service, state-of-the-art facility equipped to handle any medical emergency. With concurrent Level I[ii] certifications in adult trauma, pediatric trauma, and burn care, the department is accredited to treat the community's most-critically ill or injured patients.[17] [18]

Like most hospital emergency rooms, the ED operates 24 hours a day, 365 days a year. Although staffing levels vary to reflect expected patient volume, the department provides exceptional depth of coverage at all times, including five to six emergency medicine physicians on duty during the day and two at night, a full team of onsite trauma surgeons, committed radiology support, an Acute Psychiatric Service, and a dedicated laboratory support staff.[17] Occupying nearly 38,000 square feet in total, the department spans the ground floors of three separate buildings and is divided into six treatment areas that each accommodate a different severity or type of condition. Each year, the ED cares for over 100,000 patients and accounts for 51 percent of all inpatient admissions.[17] As illustrated in Figure 1-1, the volume of ED visits has steadily increased over the last five years.

[ii] Trauma center designations are determined at the state or local level and refer to both the kinds of resources available and number of patients admitted yearly. Level I is the highest of the five possible designations, meaning Level I trauma centers can provide total care for every aspect of injury.[18]

Figure 1-1: Volume Growth of ED Visits



* Chart adapted from the FY16 MGH ED Statistics Report.

Upon arriving to the ED, virtually all patients meet with a nurse to be triaged, or briefly assessed and prioritized based on clinical need. Patients with evidently serious conditions (e.g., cardiac arrest) will bypass this step and proceed directly to the appropriate treatment area, while patients with less severe conditions (e.g., bone fractures) will continue to an evaluation area. Once examined by an ED attending physician, patients will either be treated and released to return home, transferred to another facility for continued treatment, sent for short-term monitoring on one of two ED Observation units, or admitted to one of the many medical services within MGH (e.g., General Medicine, Neurosurgery, etc.).

1.4 Boarder Patients

For those requiring admission to the hospital, if no inpatient bed opens within two hours of an ED provider's decision to admit, the patient will continue to "board" in the ED until one becomes available (these individuals are aptly labeled *boarder patients*, or simply *boarders* for short). With limited overflow space and just 66 permanent beds in the department,[19] the crowding that often results from this practice can significantly impair ED patient flow, subsequently delaying treatment, overtaxing department staff, and in some cases triggering inferior patient outcomes. When crowding becomes severe enough to activate emergency management protocols, ad hoc staff meetings and abrupt resource reallocations pull clinicians away from their other responsibilities, imposing direct and indirect costs throughout the hospital.[20]

Under some circumstances, doctors from the Medicine Department's boarder service will take responsibility for the patient's care while they are still waiting in the ED. In such cases, the patient is labeled a *covered boarder*. This arrangement places even more stress on the system because it requires a separate team of boarder service physicians to be stationed in the department, not only commanding more resources, but also intensifying work flow complexity.

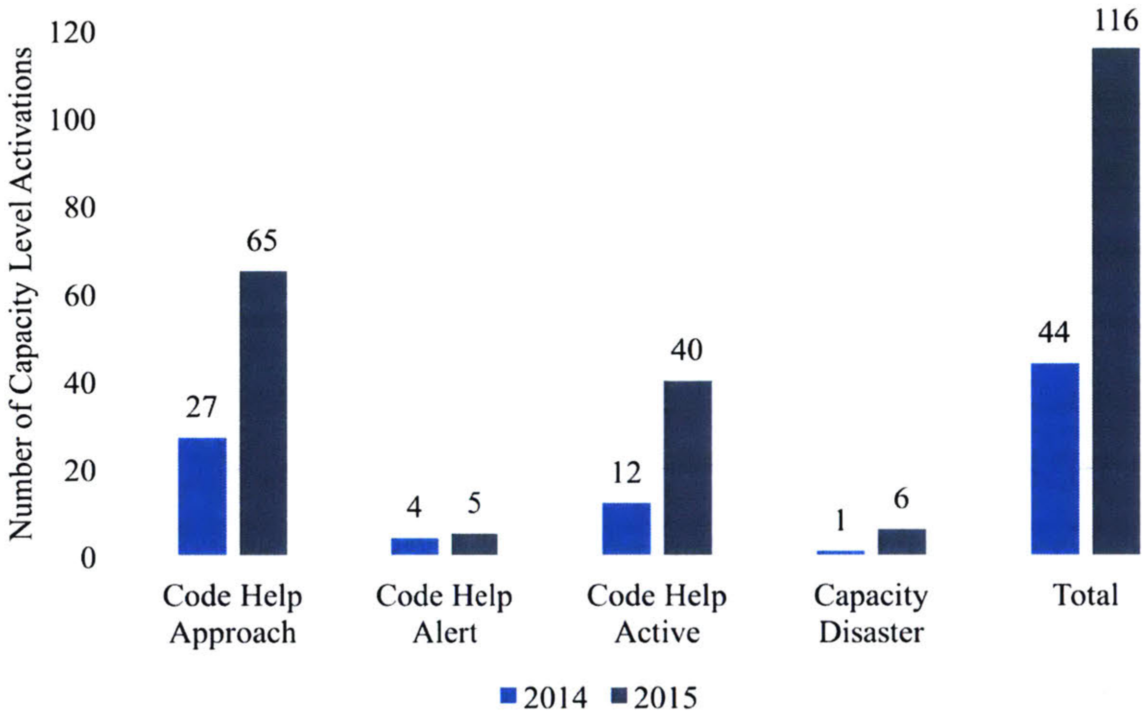
1.5 Project Motivation

Despite efforts to address capacity constraints with a massive expansion beginning less than five years ago, the ED is again displaying consistent and serious symptoms of overcrowding, including rising patient wait times and routine activation of capacity-related emergency management protocols. In 2015, the average ED boarding time (defined as the number of hours from the time an inpatient bed is requested to the time the patient is moved from the ED to an inpatient floor) increased 20 percent over the previous fiscal year to reach 3.1 hours per patient.[21] Regrettably, that spike was not the result of a few outliers. In fact, 80 percent of all patients admitted in 2015 were forced to board in the ED (i.e., wait more than two hours after the admission decision) before moving to an inpatient bed, up from 74 percent the year before.[22]

As illustrated in Figure 1-1, this increase in boarders led to a staggering 164 percent spike in the number of times the hospital reached *Code Help* or *Capacity Disaster* status.[22] These codes, [iii] which are mandated by the Massachusetts Bureau of Health Care Safety and Quality, are activated when there are boarders present in the ED and the department is either unable to care for existing patients in, or accept new patients to, a licensed treatment area.[23]

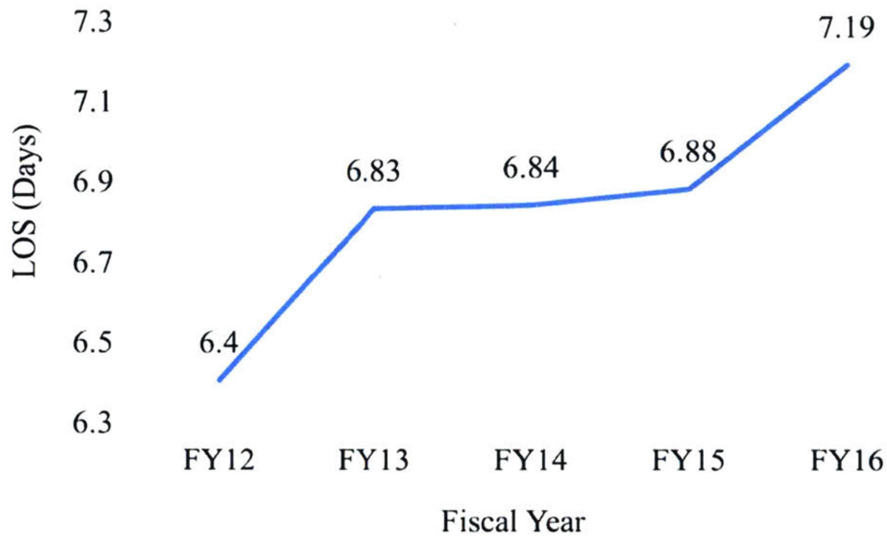
[iii] *Code Help* occurs when: i) there are patients boarding in the ED (i.e. waiting in the ED for an inpatient bed for more than two hours), ii) the Acute treatment area is full, with no patients scheduled to move out, and iii) more than five patients are waiting for any treatment area. *Capacity Disaster* occurs when: i) the ED has been in Code Help for more than two hours, and ii) patients are still boarding in the ED. The details of these and the various other ED capacity levels are summarized in Table 3-2.

Figure 1-1: Capacity Level Activations



While these symptoms are driven, in part, by a steady rise in ED visits (volume grew 18 percent in the past five years),[22] evidence suggests that downstream capacity bottleneck, especially among the hospital's General Medicine floors, is a key root cause of the increasing patient wait times. Services like General Medicine have not only experienced a surge in overall patient volume (with inpatient admissions up ten percent in the past five years),[24] but have also received a greater proportion of high-intensity, complex-care patients who remain hospitalized longer than their less complex counterparts.[25] Figure 1-2, which shows that the average length of stay (LOS) for Medicine patients rose 12.3 percent since 2012,[24] serves to illustrate this point.

Figure 1-2: Average Length of Stay (LOS) for General Medicine Patients



To further exacerbate the problem, approximately 30 to 45 inpatient beds remain unutilized at any given time because shared rooms limit the hospital's ability to collocate patients. Prohibiting factors related to this problem include patient gender, infectious conditions such as MRSA or the flu, and disruptive behavior, including that associated with mental health or substance abuse issues. Ultimately, the trends associated with patient volume, care complexity, and bed assignment have resulted in inpatient occupancy levels consistently hovering between 95 and 100 percent.[22]

The impact of such high utilization levels is suffered throughout the hospital, with many departments reporting increased levels of patient dissatisfaction (due to excessive wait times), higher attrition among non-resident physicians,[20] and growing concerns about quality and safety.[22] These capacity challenges make it critical to ensure that the patients admitted through the ED for inpatient care at MGH are those who truly need it most.

1.6 The Capacity Task Force

To address escalating capacity issues, MGH launched the Capacity Task Force in January of 2016. Comprised of hospital administrators, clinicians, data analysts, and members of the MGH-MIT Collaboration, the group was charged with identifying the best ways to alleviate immediate capacity challenges, while also developing strategies to meet the hospital's longer-term capacity demands. To provide further clarity of scope, the task force was divided into three work groups – one focused on avoidable ED and inpatient care, a second focused on preventable readmissions, and a third focused on delays related to patient placement and bed allocation.

The project described in this document resides within the first work group, also known as Capacity Task Force 1. Chaired by the Chief of Emergency Medicine, Dr. David Brown, and facilitated by the Executive Director of Emergency Services and Emergency Preparedness, Mr. Robert Seger, the group seeks to: i) efficiently and reliably identify avoidable admissions, ii) accurately quantify their impact on hospital operations, and iii) develop effective strategies for reducing their frequency.

1.7 Project Goals

As MGH grapples with mounting capacity challenges, it is imperative to understand precisely what is driving the volume growth of ED visits and inpatient admissions through the ED. Once this is clear, we further assess if any of these visits or admissions can be prevented.

Ultimately, the goal is to reduce the operational strain and increased costs associated with overcrowding, while still preserving patient safety and quality of care.

Although most patients admitted to MGH require the hospital's unique and highly-specialized treatment capabilities, some admissions can achieve equivalent or even superior outcomes by pursuing alternative care paths. These patients, termed avoidable admissions, are not admitted by mistake, but because circumstances make it difficult or impossible to coordinate the appropriate level of care elsewhere at the time of admission. Two pertinent examples include limited access to outpatient resources or a lack of appropriate clinical expertise in community hospitals.

Since avoidable admissions place unnecessary demand on hospital resources, a major focus of this project is to study the appropriateness of admissions through the ED, with special emphasis on identifying patients whose treatment can be shifted to a more appropriate care setting, whether that be in their own homes, within other community hospitals, or at other outpatient facilities. Ultimately, the goal is to improve quality of care at MGH by reducing the number of bed-days consumed by patients who could be cared for as well, or even better, in other care settings.

1.8 Main Hypotheses

The biggest challenge in addressing avoidable admissions lies in identifying which cases are in fact avoidable. As it currently stands, clinicians must review each case individually (and retrospectively) to determine if a patient could have been more-appropriately treated in another facility. Since this process is both labor-intensive and time-consuming (not to mention subjective), it severely limits the hospital's ability to perform any macro-level analysis of the problem. To remedy this, this project develops an automated method for labeling avoidable cases.

With this objective in mind, the project explores two main hypotheses. The first is that avoidable admissions are especially prevalent among patients who begin their treatment in other medical facilities before transferring to the ED at MGH. If true, this could prove particularly helpful in reducing patient congestion because: i) transfers are growing disproportionately relative to other patient populations, and ii) MGH can readily influence the number of transfers it receives. This can be accomplished strategically, by altering the terms of existing partnership agreements, or operationally, by deploying resources to community hospitals and refusing to accept transfer requests that are not fully necessary.

The second premise is that avoidable admissions strongly correlate with patients who receive unusually low levels of physician care[iv] while they are admitted to MGH. To test this theory, hospital order data is used to determine the level of care patients receive. This is appropriate given that hospital orders provide the most-detailed record possible regarding the resources and activities that are applied to patients during their hospital stays. This data is analyzed using both supervised and unsupervised learning methods to determine if avoidable admissions can be reliably identified. Once a suitable identification methodology is established, it is utilized to study the population of avoidable admissions and generate potential interventions. These include the use of analytics to identify opportunities in a more rigorous and consistent

[iv] These patients are not seen extensively by doctors, nor do they receive extensive diagnostic and/or care resources while they are hospitalized, indicating they could achieve similar outcomes in alternative care settings.

manner, as well as expanded use of telemedicine and other technologies to help shift the care of certain inpatient admissions to other, more appropriate care settings.

1.9 Key Results

This project establishes three main insights. With respect to the first hypothesis, the study concludes that avoidable admission candidates are, in fact, prevalent among patients who transfer to the ED from other medical facilities. In fact, on any given day, almost six percent of the hospital's General Medicine capacity[v] is depleted by transfer admissions who are likely avoidable. Furthermore, the growth associated with these patients is equivalent to 1.3 percent of all General Medicine beds available. Considering that MGH typically experiences utilization rates between 95 and 100 percent, and that General Medicine is among the hospital's most-heavily-utilized departments, these results inspire serious concern regarding the frequency of avoidable admissions among the transfer population.

As a first step in addressing this concern, a scorecard is developed to assist MGH in identifying and more thoroughly understanding the facilities whose transfer patients consume the most hospital capacity with respect to their peers. Since the information encompassed in this scorecard is not always transparent, MGH is encouraged to use it as a tool to initiate cooperative dialogues with partner facilities.

In relation to the second hypothesis, unsupervised and supervised learning methods reveal that even generalized order data can identify avoidable admission candidates (by using

---

[v] According to the hospital's Admitting Department, General Medicine contains a total of 230 beds.

ambulatory care-sensitive conditions[vi] as a proxy for patients that can achieve favorable outcomes in other care settings) with relatively high certainty. Random forest[vii] and logistic regression[viii] methods achieve an average AUROC[ix] of 0.76 (and, in some cases, reach values as high as 0.85) when attempting to identify conditions traditionally associated with avoidable admissions. Considering that a score of 1.0 reflects a perfect classification model, this validates the hypothesis that order data can be used as a proxy for a patient's level of care and suggests it can serve well to further investigate avoidable admissions.

Lastly, a scoring method is developed in collaboration with hospital physicians to automatically identify avoidable admission candidates using more detailed order data. Together, these patients consumed 1,920 bed days in FY15, or an average of five beds per day. Due to time constraints, the results of this methodology could not be verified via manual case review, but the preliminary results provide a strong basis for future work.

1.10 Thesis Organization

Following this introduction, Chapter 2 continues with a literature review summarizing research on avoidable admissions and ambulatory care-sensitive conditions. Chapter 3 then

---

[vi] Ambulatory care-sensitive conditions are conditions for which timely and appropriate outpatient care can potentially prevent the need for hospitalization.[32] This concept is discussed in more detail in Chapter 2.

[vii] Random forest is an ensemble learning method for classification that functions by constructing a multitude of decision trees and then reporting the classification that is the mode of the individual trees. Creating many decision trees and randomly selecting the features at each tree node helps control for variance.[70]

[viii] Logistic regression is a statistical method used to analyze a dataset in which there are one or more independent variables that determine some binary outcome.[71]

[ix] The area under the receiver operating characteristic curve (AUROC) is used to measure the performance of a binary classifier. This is discussed in more detail in Chapter 5.

provides a detailed description of the ED's physical organization and patient flow, as well as supplemental background information. Chapters 4 and 5 summarize the methodologies and key findings stemming from the project's analyses of transfers and short-stay patients, respectively. Finally, Chapter 6 concludes the thesis with a summary of recommendations and suggestions for future research.

This page intentionally left blank

Chapter 2

Literature Review

This chapter summarizes selected research in areas relevant to the major topics of this project. These include avoidable admissions and ambulatory care-sensitive conditions.

2.1 Avoidable Admissions

There is an abundance of literature dedicated to the topic of avoidable admissions. Yet most studies approach the topic from an entirely different perspective and purpose than the effort described in this document. To be specific, rather than examining hospital patients who could have achieved equivalent outcomes in lower care settings, research conducted over the last decade has overwhelmingly considered avoidable admissions as a means of measuring access to non-hospital care, particularly general practice. [59] [62] As Laditka et al. discuss in a study linking insurance status to avoidable admissions, this approach centers on a long history of concern that poorer Americans lack access to primary health care.[62]

Underlying the more common view of avoidable admissions is the notion that hospitalizations for certain medical conditions, termed ambulatory care-sensitive conditions (ACSCs), can be avoided with timely and effective outpatient care.[59] Those adopting this approach label any ambulatory care-sensitive hospitalization (ACSH) as potentially preventable and use the rate of ACSHs as an indicator of a community's access to primary care.[59]

Despite the popularity of using ACSHs to gauge access to care, the assumptions underlying this practice are often disputed. Weinberger et al., for instance, point out that higher rates of hospitalization may, in fact, reflect *better* access to primary care since appropriate referrals often stem from issues identified in the primary care setting.[26] In another study, Manski et al. discovered that while most patients hospitalized for Type II Diabetes did live in locations with less access relative to other areas, patients still maintained good access to general practice, with three-quarters reporting they were typically able to see their primary care physician (PCP) within 24 hours. The study conjectured that what could be more important than the promptness or frequency of PCP interactions is the quality of the consultations.[59] Countering this perspective, however, Freund et al. cite the abundance of factors outside direct physician control, including low socioeconomic status, cultural background, and older age, as reason to doubt the assumption that optimal primary care can prevent ACSHs.[27]

The fact that so many underlying assumptions are contested highlights the complex causality associated with avoidable admissions. Indeed, there are so many characteristics that may potentially influence ACSH rates, it becomes virtually impossible to decouple them. Considering those related to general practice alone, there is accessibility, quality of care, continuity of care, the caseload of practitioners, and patient satisfaction with care, to name a few.[28] As Muenchberger et al. point out, there are also many factors unrelated to general practice that need to be considered, including patient age, gender, low socioeconomic status, ethnicity, social support, household crowding, number of medications, non-compliance to medication, and low self-reported health status.[28]

Expanding on these insights, Sanmartin et al. conclude it is difficult to determine the extent to which many ACSHs are avoidable given the progressive course of many chronic conditions and the impact of multimorbidity.[29] Furthermore, according to Moy et al., even if the various causes could somehow be isolated, analyses still could not address causality. Rather than residence in low-income neighborhoods contributing to poorer health and hospitalization, for example, poorer health might lead to residence in low-income neighborhoods.[30] Despite these issues, much of the existing literature approaches avoidable admissions from an exceedingly narrow perspective. Thorpe et al., for instance, analyze rural-urban differences in avoidable admissions among veterans with dementia,[31] while Nayar et al. examine the relationship between ACSHs and the proportion of non-physician clinicians in certain geographic areas.[32]

Those studies that do take a more macro-level approach, however, agree on two main points. The first is that avoidable admissions are common. In a study conducted by Ouslander et al., 68 percent of hospitalizations for nursing home residents were rated as "probably" or "definitely" not the lowest level of care required to meet the patient's needs.[65] In a study focusing on adverse drug reactions, Beijer et al. found that 88 percent of the admissions were avoidable.[33] And in separate studies, Assuli et al. and Freund et al. concluded that 50 percent and 41 percent of all readmissions were avoidable, respectively.[27 60] The second main point of agreement is that avoidable admission rates are declining. In studying trends associated with preventable inpatient hospital admissions and ED visits, Fingar et al. estimated that ACSHs decreased 25 percent from 2000 to 2012.[34] Likewise, Moy et al. cited a decrease across all income quartiles from 2001 to 2009.[30]

Unlike previous work involving avoidable admissions, this study integrates multiple hospital data sources and leverages a completely new one (i.e., order data). The result is an attempt to determine level of care by examining the specific care resources and activities applied to hospital patients as opposed to simply investigating the correlations between avoidable admissions and various patient characteristics.

2.2 Ambulatory Care-Sensitive Conditions and Hospitalizations

While there is not universal agreement regarding the conditions that qualify, Appendix A captures the seven that were most-commonly labeled ACS in the literature reviewed for this study,[60] [61] [62] [63] [64] as well as their corresponding ICD9[x] codes. The seven conditions include: i) bacterial pneumonia, ii) cellulitis, iii) chronic obstructive pulmonary disorder (COPD), iv) dehydration, v) diabetes, vi) heart failure, and vii) urinary tract infection (UTI). These will be employed later in the analysis portion of this document.

Although ACSHs do not perfectly align with this project's definition of avoidable admissions, research does indicate a strong correlation between ACSHs and hospital patients who could be appropriately treated in lower care settings. In a study of nursing home residents, for example, Ouslander et al. conclude that 95 percent of hospitalizations rated retrospectively by physicians as potentially avoidable were for ACSCs.[65] Further supporting this view, research conducted at MGH by Ticona et al. reveals a strong correlation between ACSCs and ED patients identified as candidates to be discharged with home care services (as opposed to being admitted).[66]

---

[x] The ICD9 (International Classification of Diseases, Ninth Revision) is a healthcare classification system. It consists of a set of alphanumeric codes used to classify diagnoses.

Chapter 3

ED Patient Intake, Flow, and Supplemental Information

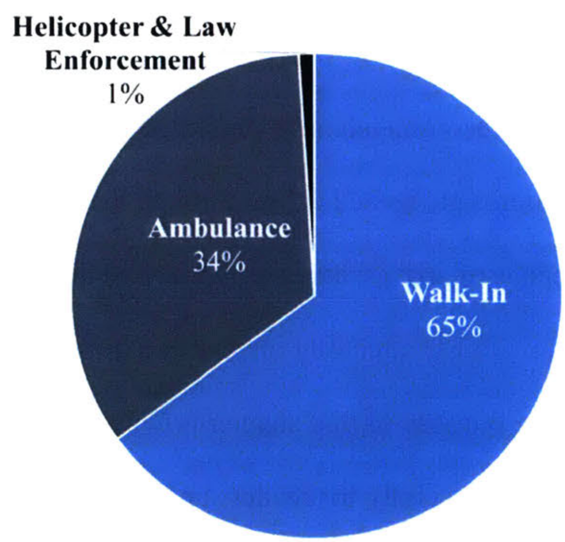
Many of the analyses and recommendations presented in this document rely heavily on a basic understanding of how patients are routed to and through the ED at MGH. This includes familiarity with the various means of arrival, care pathways, and dispositions for patients, as well as the considerations involved in an ED attending physician's decision to admit (or not admit) a patient to the hospital. Thus, the purpose of this chapter is to contextualize the information presented in subsequent chapters, especially for readers unfamiliar with MGH or healthcare in general.

3.1 Patient Means of Arrival

Patients arrive to the ED by one of four means: i) walk-in, ii) ambulance, iii) helicopter, and iv) law enforcement. Both law enforcement and helicopter arrivals are rare, together constituting less than one percent of all ED arrivals in FY15.[35] Ambulance arrivals, which include anyone transported to the hospital by a private ambulance service, make up 34 percent of

ED patients.[35] Finally, walk-ins are the largest category, contributing 65 percent of all ED arrivals.[35] The term walk-in is somewhat of a misnomer because it encompasses everyone who does not arrive via one of the other means listed. This includes patients arriving by foot, personally-owned vehicle, public transportation, or taxi. Figure 3-1 captures the distribution of ED patients by their means of arrival.

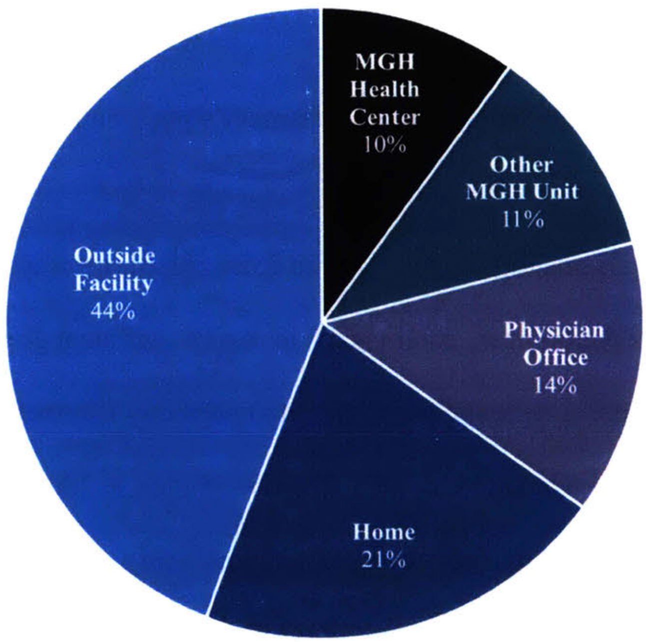
Figure 3-1: Distribution of ED Patients by Means of Arrival



3.2 Patient Referral Source

In addition to tracking means of arrival, the ED also monitors the referral or transfer source for any patient who contacts the department before arriving. FY15 data shows that calls are received from several sources, including patients' homes (21 percent), physician offices (14 percent), other units at MGH (11 percent), and MGH health centers (10 percent). However, the largest portion of calls come from outside medical facilities (44 percent). Furthermore, this statistic is growing disproportionately, having increased eight percent during the previous year alone. Figure 3-2 illustrates the distribution of ED patients by referral source.

Figure 3-2: Distribution of ED Patients by Referral Source



3.3 ED Layout and Patient Flow

In general, the ED routes visitors through three initial steps – i) Reception, ii) Triage, and iii) Evaluation – before determining if they should proceed to one of the department's six treatment areas – i) Acute, ii) Urgent, iii) Fast Track, iv) the Clinical Decision Unit (CDU), v) the Acute Psychiatric Service (APS), and vi) the Pediatric Emergency Department (PED). In some cases, patients requiring immediate medical attention bypass these steps altogether, but everyone who ultimately proceeds to a treatment area is assigned based on the type or severity of their condition. Figure 3-3 outlines the general flow of patients through the department. Each of the nine main areas is then detailed in the following sections.

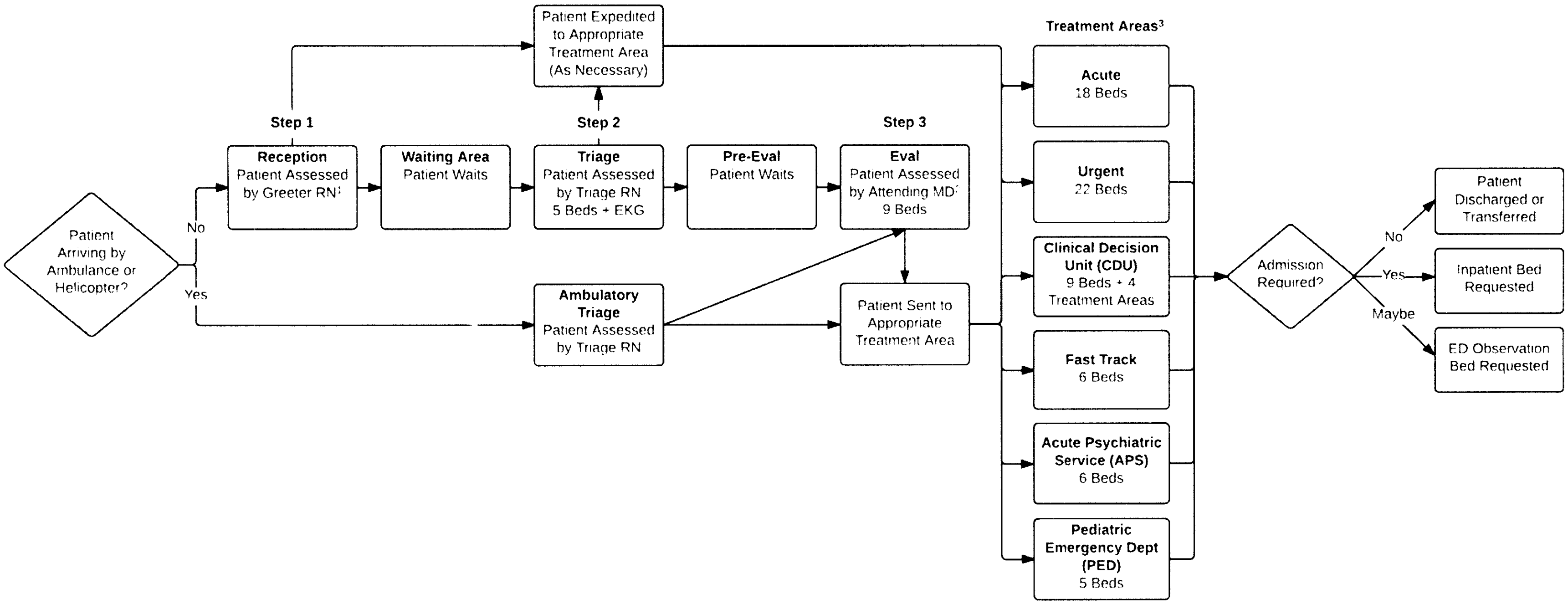
3.3.1 Reception

Reception is located just beyond the department's main entrance. Since patients transported to the hospital via ambulance or helicopter use separate entryways, Reception is normally reserved for walk-ins or patients referred from one of the outpatient clinics on campus. Upon arriving to the Reception desk, each visitor is met by a clinical greeter, or Greeter Nurse, who makes an initial assessment and guides the patient directly to a treatment, screening, or waiting room. The Greeter Nurse role, which was first piloted in 2007 as part of a patient flow redesign initiative, expedites diagnostic testing and significantly reduces patient wait times. Under this format, patients often see a caregiver within minutes of entering the department.

3.3.2 Triage

Since patients can present to the ED at any time and with any complaint, a key function of the department is the prioritization of cases based on clinical need. This process, called triage, is accomplished in one of five screening bays located adjacent to the ED's reception area. Triage is generally the first stage that a patient passes through after registering with the Greeter Nurse.

Figure 3-3: ED Patient Flow Diagram



[1] RN is the abbreviation for Registered Nurse

[2] MD is the abbreviation for Medical Doctor or Physician

[3] Patients are shifted between the different treatment areas as necessary due to the evolving nature of medical conditions

Lasting about five minutes, it consists of a brief assessment that includes measuring the patient's vital signs and assigning a chief complaint (e.g., abdominal pain, difficulty breathing, etc.).

Triage is most often conducted face-to-face when the patient presents to the ED, but a form of triage may also be conducted via radio with an ambulance crew. This is called a Central Medical Emergency Direction (CMED) call.[36] Reserved for sicker patients, it enables paramedics to provide the hospital with a short update regarding an incoming patient so the individual can be triaged to the appropriate level of care immediately upon arrival.

3.3.3 Evaluation (Eval)

Excluding those identified as requiring immediate attention, most patients proceed from Triage to Pre-Evaluation (Pre-Eval), where they will wait until one of nine Evaluation (Eval) rooms becomes available. Typically staffed by a nurse, two attending physicians, and four physician assistants (PAs), the Eval team will conduct a more thorough assessment of the patient, which could include imaging or lab testing. Based on the results of this examination, patients will be sent to one of the six treatment areas within the ED, treated and released to return home, or in some cases, transferred to an external medical facility for ongoing care.

3.3.4 Acute

The Acute area treats the department's most-seriously ill or injured patients. It consists of 16 rooms, including three state-of-the-art, critical care resuscitation rooms. Typical staffing includes one attending physician and at least one, but usually two, nurses with Trauma and Advanced Cardiac Life Support (ACLS) training. Acute cases may also be attended by residents, radiographers, ambulance personnel, respiratory therapists, and hospital pharmacists, depending upon the skill mix required for any given case. Once stabilized, patients are generally admitted to one of the medical services within MGH (e.g., General Medicine or Neurosurgery).

3.3.5 Urgent

Patients who exhibit signs of being seriously ill or injured but who are not in immediate danger of life or limb will be triaged to one of the Department's 22 Urgent beds, where a physician will perform a more thorough assessment and treatment. Examples of Urgent cases include chest pain, difficulty breathing, abdominal pain, and neurological complaints. Advanced diagnostic testing may be conducted during this stage, including laboratory testing of blood or urine, ultrasonography, CT, or MRI scanning. Medications appropriate to manage the condition will also be administered. Depending on the underlying causes of the chief complaint, Urgent patients may be discharged home or admitted to the hospital for further treatment.

3.3.6 Clinical Decision Unit (CDU)

The Clinical Decision Unit (CDU) provides an alternative to discharge or inpatient admission for patients who may benefit from additional monitoring or diagnostic evaluation prior to disposition. The section is made up of nine beds and four treatment areas, each containing a set of chairs. Three treatment areas are identical, while the fourth is specifically designated for psychiatric patients. Clinical observers are employed to ensure that psych patients remain in the CDU and to prevent them from harming themselves or others.

Some of the most common symptoms and conditions sent to the CDU include chest pain, atrial fibrillation, congestive heart failure, back pain, dehydration, gastroenteritis, and trauma. About half of all CDU patients are ultimately treated and released from the hospital, with most of the remaining half being admitted to either an ED Observation floor (where they will continue to be monitored for up to 24 hours) or to one of the hospital's inpatient medical services. Because it offers an opportunity for further evaluation and treatment, the CDU can help prevent unnecessary hospital admission or negative outcomes due to premature discharge.[37]

3.3.7 Fast Track

Fast Track is an area dedicated to patients with minor, non-life-threatening injuries and illnesses, such as rashes, lacerations, or the flu. Consisting of six beds, this minor care area significantly improves the flow of patients through the department, reducing wait times and increasing both patient and staff satisfaction.[38] Ideally, Fast Track patients are discharged within 60 to 90 minutes of seeing a provider.

3.3.8 Pediatric Emergency Department (PED)

The Pediatric Emergency Department (PED) is an area dedicated to the treatment of infants, children, and adolescents under the age of 19. Since treating young people can present unique challenges, it is staffed primarily with board-certified specialists in Pediatric Emergency Medicine[39] and boasts several features specifically designed to help minimize patient stress. These include a colorful treatment area stocked with iPads and toys, as well as six child-friendly, private rooms featuring their own televisions and DVD players. Patients also benefit from the presence of Child Life Specialists, who leverage play and age-appropriate education to help children and their families cope with hospital-related anxiety. In total, the PED cares for over 14,000 patients a year.[39]

3.3.9 Acute Psychiatric Service (APS)

The Acute Psychiatry Service (APS) addresses acute psychiatric, neuropsychiatric, and substance-use emergencies in both children and adults. The area's main objectives are to stabilize patients and refer them to the appropriate follow-on treatment, either within MGH or elsewhere. The APS is staffed by attending psychiatrists with expertise spanning many disciplines, including addiction treatment, child psychiatry, and psychosomatic medicine.[40] The department, which also incorporates psychiatric residents, psychology interns, social workers, and security personnel, typically sees more than 6,000 patients a year.[40]

3.4 Network Development and Integration

The MGH Network Development and Integration Department cultivates new relationships and expands upon existing affiliations with outlying regional hospitals, physician groups, and healthcare systems.[52] These relationships vary in terms of their focus (e.g., clinical, educational, research) and can take a variety of forms, including bundled-payment programs, consulting services, remote medicine, collaborations, clinical affiliations, joint ventures, and mergers, just to name a few.[41] Ultimately, Network Development efforts help the institution's various programs and clinical initiatives reach patients and physicians in the community, but they also play an important role in driving the volume and mix of patients that visit MGH each year (a key to sustaining and increasing the organization's operational revenue and profits). Understanding this function is critical to interpreting the analyses presented later in this document.

3.4.1 Motivations

Fostering a relationship with MGH appeals to community hospitals for many reasons. For one, it provides an opportunity to build new capabilities that deliver essential competitive advantage. For example, in a deal struck with Steward Medical Group in 2012, MGH agreed that Partners physicians would help several Steward hospitals gain the Level 3 certification required to take on less-acute trauma cases.[43] While not a strong revenue generator, trauma care is considered a crucial measure of a hospital's skills and competence, which undoubtedly helped make the deal enticing to Steward.

This conjures a second key motivator for establishing connections to MGH: improving one's brand and reputation. As Stuart Altman, professor of health policy at Brandeis University, commented on the trauma partnership, "Steward is trying to develop a full-service system so they have the capability to provide [health services] that anyone would want... And to the extent that they can't provide those services, they're trying to show that their brand is developing ties, and has access, to high-end institutions."[43]

A third key benefit for community hospitals is knowledge sharing. As Dr. Michael Callum, president of Steward Medical Group, said of the trauma affiliation, "It will create a new level of communication between our organizations, including direct links between emergency physicians in our community hospitals and trauma physicians at Massachusetts General Hospital."[43] One of those direct links involved sending surgical residents to MGH for trauma care training.

Of course, hospital partnerships are reciprocal arrangements, with MGH receiving many important benefits from them as well. For one, alliances often shift patients from competing hospitals, as did the Steward agreement with respect to trauma patients from Beth Israel Deaconess, Boston Medical Center, and Tufts.[43] In addition to building market share, hospital affiliations help shepherd high-complexity, high-margin patients to specialty services that would otherwise risk being underutilized. The importance of this function to maintaining the financial well-being of the hospital cannot be understated.

Finally, network development efforts contribute to the community service component of the hospital's mission.[42] As Ann Prestipino, a senior vice president at MGH, commented at the time of the Steward deal, "This provides us an opportunity to be altruistic in sharing our knowledge about treating some of the most critically sick and injured patients. And we're developing a relationship with a group of community hospitals that need our help."[43]

3.4.2 Relationship Tiers

Driven by the motivations just discussed, MGH maintains partner agreements with some 93 other healthcare institutions. Based on the details of these agreements, each partner facility is assigned to one of five tiers reflecting the strength of the facility's affiliation to MGH. Listed in order of priority, the tiers are: i) MGH Subsidiaries, ii) PHS (Partners HealthCare System) Family, iii) Incremental Affiliates, iv) Other Affiliates, and v) Unaffiliated Facilities. These tiers, which are discussed in further detail in Chapter 4, greatly influence the volume and mix of patients who transfer to MGH from other facilities.

3.5 The Clinical Access Program

The Clinical Access Program serves many functions within MGH, to include tracking and reporting referrals to specific services, performing quality assurance for imaging and labs, and following up with patients who are treated and released from the ED. Most relevant to this study, however, is the task of fielding inter-hospital transfer requests by phone or electronically via the hospital's Customer Relationship Management System. Originating from over 200 different facilities, transfers typically represent 9 percent of the total ED volume or an average of

25 patients per day.[35] The staff responsible for managing these requests consists of an Access Nurse or Physician's Assistant during the day and the Urgent Attending Physician or ED Referral Coordinator at night. To understand how this group decides whether to accept or refuse a transfer request, it helps to first review a key piece of legislation that largely impacts their decision criteria.

3.5.1 The Emergency Medical Treatment and Active Labor Act (EMTALA)

The Emergency Medical Treatment and Active Labor Act (EMTALA) is a federal statute that Congress enacted in 1986 as part of the Consolidated Omnibus Budget Reconciliation Act of 1985.[44] In short, the law requires participating hospitals to screen, stabilize, and treat the emergency medical condition of anyone seeking care, regardless of their insurance status or ability to pay.[44] Sometimes referred to as the "anti-dumping law," EMTALA's purpose is to prevent private hospitals from transferring patients who are either uninsured or covered under Medicare or Medicaid to public hospitals without first verifying that they are safe for transfer.[44]

Although limited to "participating hospitals," EMTALA pertains to any facility that accepts government reimbursement for services provided to Medicare or Medicaid beneficiaries. This means the legislation applies to virtually every hospital in the United States, excluding only those operated by the military or Shriners International, which owns a network of non-profit facilities.[45] The law is also significant in that it protects *all* patients, not just those receiving Medicare or Medicaid benefits.[46]

For many reasons, hospitals are strongly motivated to comply with EMTALA. Penalties for violating the statute can include termination of a hospital's Medicare provider agreement and fines of up to $50,000 per violation.[44] Violators may also be sued in civil court for personal injury or for causing financial harm to another medical facility.[46] Considering that 51 percent of MGH's total ED volume in FY15 was either Medicare or Medicaid beneficiaries, the hospital has good reason to emphasize EMTALA compliance.[35]

Where EMTALA is especially relevant to the Access Program is in how it governs inter-hospital transfers. Namely, it dictates that hospitals with specialized capabilities, such as burn units, shock-trauma units, or neonatal intensive care units, are obligated to accept transfers from other hospitals so long as they have the capacity to treat the patient and their capabilities exceed those of the referring hospital.[47]

3.5.2 Transfer Acceptance Guidelines

Influenced primarily by the EMTALA provisions just described, the ED utilizes three general guidelines for evaluating transfer requests: i) the patient's diagnosis group, ii) the capacity state of both the ED and the required medical service (if known) at the time of the request, and in limited cases, iii) the specific hospital group involved. These criteria are ultimately incorporated into a transfer algorithm (covered in Section 3.5.3) that delineates specifically how each transfer request must be handled.

3.5.2.1 Diagnosis Group

The first guideline is fitting because the diagnosis group indicates if a patient's condition requires a higher level of care relative to the transferring facility. To facilitate EMTALA compliance, the Access Program maintains the list of "Just Say Yes" diagnosis groups captured in Table 3-1. Because each requires specialized resources within MGH, staff members are advised to do everything possible to accept patients exhibiting these diagnoses. Servicing these conditions also provides tremendous financial benefits for the hospital, which further underscores their importance.

Table 3-1: "Just Say Yes" Diagnosis Groups

Diagnosis Group	Description
Trauma	Any injury that has the potential to cause prolonged disability or death, often involving falls, motor vehicle collisions, or gunshot wounds
Burn	Injury to the skin, or other tissues, caused by heat, cold, electricity, chemicals, friction, or radiation
Abdominal Aortic Aneurysm (AAA)	A heart condition that occurs when an area of the aorta becomes very large or balloons out[48]
Subarachnoid Hemorrhage (SAH)	A condition that involves internal bleeding into the area between the arachnoid membrane and the pia mater surrounding the brain[49]
ST-Elevation Myocardial Infarction (STEMI)	A type of heart attack that occurs when a blood clot completely blocks an artery in the heart[50]

3.5.2.2 Capacity State

The next guideline for evaluating transfer requests involves assessing the capacity state of both the ED and the required medical service (if known) at the time of the request. To aid in gauging ED capacity specifically, the Access Program defines six ED Capacity Levels, which are detailed in Table 3-2. In accordance with a mandate by the Massachusetts Bureau of Health

Care Safety and Quality, MGH must notify the state whenever the hospital activates the two highest capacity levels, Code Help or Capacity Disaster.

Table 3-2: ED Capacity Levels

Capacity Level	Description
Open	· ED open (beds available)
Caution	· ED full (no beds available)
Approaching Code Help	· Patients boarding in ED · Acute treatment area full · > 2 patients waiting for any treatment area
Code Help Alert	· Patients boarding in ED · Acute treatment area full · > 5 patients waiting for any treatment area
Code Help Active	· Patients boarding in ED · Acute treatment area full, with no patients scheduled to move · > 5 patients waiting for any treatment area
Capacity Disaster	· ED in Code Help Active for > 2 hours · Patients still boarding in ED

In general, if the ED Capacity Level is Approaching Code Help or worse at the time of a request, the transfer is refused. "Just Say Yes" patients enjoy a slightly higher threshold in that they are not refused unless the ED is in Code Help Active or Capacity Disaster. Even then, however, Access Program staff will contact the required service to see if the patient can be admitted directly.

For all other transfers requiring specific services, such as the ICU, Pediatrics (Pedi), or Obstetrics (OB), the Access Program staff will also check the capacity state of that service before allowing a patient to transfer to the ED. If the service is on divert status, meaning the department is full and no longer accepting new patients, the transfer is also refused.

3.5.2.3 Hospital Group

Hospital Group is another important consideration when evaluating transfer requests because MGH has agreed to accept patients from certain institutions whenever capacity is available. These "Just Say Yes" hospital groups include Steward Trauma, St. Elizabeth's Neurosurgery, and neighboring Massachusetts Eye and Ear. Again, so long as the ED has not activated Code Help or Capacity Disaster, transfers from these facilities are accepted.

3.5.3 Clinical Access Program Transfer Algorithm

Based on the general guidelines described above, the ED maintains a Transfer Algorithm that has been intentionally omitted from this document for confidentiality reasons. The algorithm is essentially a process flow diagram that spells out exactly how Access Program staff should evaluate specific transfer requests. The algorithm also includes contact information and instructions on how to reach the various hospital services and staff. Despite the detailed nature of the Transfer Algorithm, functionally it serves more to route patients than to filter them in terms of their appropriateness for transfer. This is evidenced by the fact that, for the past three years, almost 97 percent of all transfer requests have been accepted.[35] One interesting factor that could influence this statistic is the fact that nurses often field transfer request calls from attending physicians at other institutions. This power differential can make it difficult for Access Nurses to refuse transfers, even when they are not fully warranted.

3.6 Chapter Summary

Armed with a better understanding of the various channels that direct patients to the ED, the criteria used to evaluate transfer requests, and the considerations that influence how patients are routed through the department, we can now turn our attention to the various analyses that comprise this study. The next chapter focuses specifically on transfer patients, while the following chapter considers short-stay patients, regardless of their source of origin.

This page intentionally left blank

Chapter 4

Analysis of Facility-to-ED Transfer Admissions

This portion of the analysis explores the first of two main hypotheses presented in Chapter 1. Specifically, this chapter investigates the notion that avoidable admissions are especially prevalent among patients transferred to the ED from other facilities. While this was a common perception for many hospital staff members prior to the study, no previous effort had been made to rigorously investigate it using hospital data. Thus, the objective of the methodology presented here is to comprehensively understand the nature and scope of avoidable admissions within the transfer patient population.

4.1 Data Sources and Integration

The analysis of facility-to-ED transfer admissions utilizes information from three separate hospital data sources: i) the Emergency Department Information System (EDIS), ii) Enterprise Performance Systems, Inc. (EPSi), and iii) the Network Development Relationship Database. Each source is summarized in the sections that follow.

4.1.1 Emergency Department Information System (EDIS)

The Emergency Department Information System (EDIS) is a Windows-based software platform developed to efficiently collect and manage information relevant to a patient's ED visit. Due to the immense volume of care information generated daily, this system is critical to effectively tracking and treating ED patients. While the EDIS acronym is used generically within the healthcare sector to describe a variety of software packages designed toward this purpose, here it refers to a specific system that was developed and used exclusively by MGH until the hospital adopted a more-integrated electronic medical record system known as EPIC in early 2016.

Before the EPIC rollout, EDIS provided patient tracking, computerized physician order entry (CPOE), nurse charting, and physician documentation features, among others. Because it was not replaced until this study was already underway, all the ED-specific patient and care information used in the analysis is derived from EDIS. This includes data pertaining to approximately 15,000 unique patients and 17,000 unique hospital encounters. The dataset captures significant patient attributes, such as point of origin, means of arrival, and admitting diagnosis, as well as the timing of pivotal events during the ED visit, including arrival, inpatient bed request (if applicable), and dismissal. All encounters occurred during fiscal years 2014 and 2015.

4.1.2 Enterprise Performance Systems, Inc. (EPSi)

Enterprise Performance Systems, Inc. (EPSi) is a web-based budgeting, cost accounting, and financial decision support platform that currently supports fourteen of the top eighteen U.S. hospitals.[51] At its core, the system combines vital clinical, financial, and operational data to help hospitals make informed decisions. For this project, EPSi provides data pertaining to the same 15,000 patients and 17,000 encounters identified in EDIS. All data was generated during fiscal year 2015 and entered by various providers and administrative staff over the course of each patient's treatment at MGH.

4.1.3 Network Development Relationship Database

The Network Development Relationship Database was created by the hospital's Network Development and Integration Department, a team that develops new relationships and expands upon existing affiliations between MGH and outlying regional hospitals, physician groups, and healthcare systems.[52] The database specifically contains information regarding the partner agreements that MGH maintains with some 93 other healthcare institutions. These facility affiliations serve an important role for community hospitals in that they provide complex patients access to the world-class specialty care that only an Academic Medical Center like MGH can provide. The relationships also serve an important role for MGH in that they help shepherd high-complexity, high-margin patients to specialty services that would otherwise risk being underutilized.

Since partner agreements can influence the hospital's decision to accept non-tertiary patients from other institutions (i.e., those who do not require the specialized resources unique to MGH), understanding the nature of these agreements is critical to evaluating the appropriateness of specific patient admissions. The Relationship Database provides this insight by assigning each partner facility to one of five relationship tiers. The tiers, which are detailed later in this chapter, reflect the strength of each institution's partnership with MGH.

4.1.4 Data Integration

Data from EDIS and EPSi is joined using a common field known as *Patient Account*. Since no such field exists in the Relationship Database, a facility key is manually created to associate each patient's transfer source with an existing partner agreement. Finally, all three data sources are merged into a master file used to perform the analysis.

As is typical when dealing with any large organization's data, challenges surface when analyzing the aggregated file. For example, many fields are designated as either free text or optional response. This makes it problematic to efficiently pre-process and analyze the output due to redundant or missing entries. When it is determined that one of these fields is critical to the analysis, the output is standardized using both automated and manual review methods.

Another primary issue involves inconsistencies between matching fields in different data sources. When this occurs, specific methodologies are developed in coordination with hospital staff to best reconcile the discrepancies. One example of this occurs because EDIS and EPSi do not always agree on a patient's transfer source. To address the problem, the team investigates how the information is collected in each system. Observing that the data in EDIS is staff-populated while that of EPSi is patient-reported, the team decides EDIS is more reliable. EPSi is then used only if the EDIS transfer facility appears blank.

4.2 Focus Population

Before delving into the methodology and its key findings, it is important to first establish the specific patient population included in the analysis. This group, labeled *facility-to-ED transfer admissions*, includes all patients who were evaluated in the MGH ED during fiscal years 2014 or 2015[xi] and who also met two general criteria: first, that they were transferred to the department from an external medical facility, and second, that they were subsequently admitted to an inpatient floor at MGH. In this case, an "external medical facility" could be either another hospital ED or one of many non-acute options, including a skilled nursing facility (SNF), rehabilitation clinic, or psychiatric hospital. Patients arriving from these facilities were ultimately admitted to either a General Medicine floor or to that of another medical service, such as Surgery or Neuroscience.

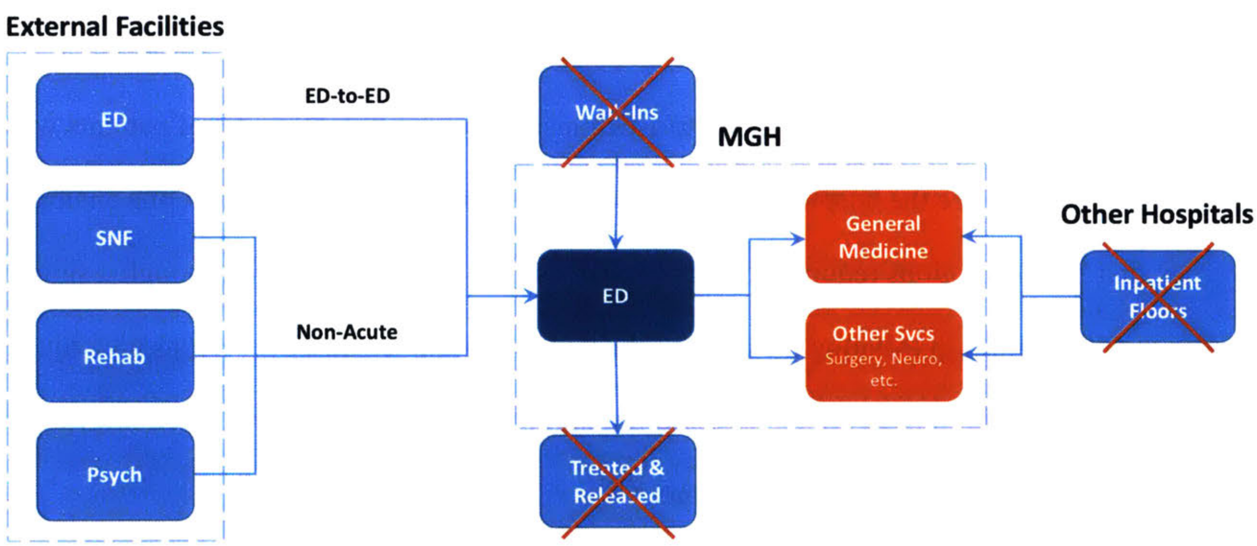
To further clarify the focus population, it helps to also discuss those who do *not* qualify as facility-to-ED transfer admissions. These include walk-ins and patients with minor conditions who are treated and released directly from the ED. Because the former does not transfer from an external medical facility and the latter is never admitted to an inpatient floor, the two groups clearly do not meet the criteria defined above. Also excluded from the focus population are patients who transfer directly from an inpatient floor at another hospital to an inpatient floor at

[xi] Each fiscal year runs from October of the previous calendar year through September of the corresponding calendar year. FY14, for example, runs from October 1st of 2013 to September 30th of 2014.

MGH. Since these patients bypass the ED altogether, they are considered outside the scope of this study. Other exclusions include patients under the age of 18 and those who expire (or die) during their visit.

Figure 4-1 depicts the focus population by diagramming their various pathways to admission. Excluded patient groups are crossed out, while facility-to-ED transfer admissions are highlighted in red.

Figure 4-1: Focus Population



4.3 Methodology

This section details the specific methods used to identify avoidable admission candidates from within the transfer patient population. All methodologies were developed in conjunction with members of Capacity Task Force 1, who provided the clinical and administrative insights to ensure they are appropriate within the context of MGH's broader operational environment.

4.3.1 Patient Qualifiers

To assess the scope of avoidable admissions among the study's focus population, we identify six, distinct patient qualifiers: i) ICU Status, ii) Medical Service, iii) Transfer Type, iv) MS-DRG Classification, v) Facility Affiliation, and vi) PCP Affiliation. These qualifiers, which will be discussed in detail in the following sections, perform like the layers of a sieve, progressively filtering the body of facility-to-ED transfer admissions to a subset of patients who are likely do not require the hospital's specialized care resources. Consistent with this analogy is the fact that both operations require a coordinated effort. In the case of a sieve, though a single screen may be helpful in isolating the coarser elements of a sample, multiple screens are required to identify the sample's finest components. Similarly, patient qualifiers have limited relevance unless implemented in a coordinated fashion.

Where the patient qualifier method deviates from the sieve analogy is in its varied approach to classification. Whereas a mesh screen always functions according to particle size, each patient qualifier is unique in how it relates to the issue of avoidable admissions. One qualifier may target patient acuity, while another addresses the limited capacity of a specific medical service or the influence of transfer agreements with other hospitals. Whatever the underlying connection, the diversity among these patient qualifiers simply reflects the complex nature of healthcare.

In that same vein, it is important to recognize that no assortment of patient qualifiers can *perfectly* identify avoidable admissions. Indeed, because of the inherent complexity involved, there is always a degree of subjectivity when evaluating admission decisions. Even manual case review by a group of doctors will not always yield identical results. Thus, the patient qualifier methodology is intended to be more directional than it is precise. To help counterbalance this lack of precision, the qualifiers are intentionally conservative, meaning they focus only on patients whose admissions are highly questionable. Also helpful is the fact that the results are interpreted from a perspective that recognizes the methodology's limitations. The following sections introduce the six patient qualifiers and explain why each is pertinent to the analysis.

4.3.1.1 ICU Status

The ICU caters to patients with severe, life-threatening illnesses or injuries that require constant monitoring, specially-trained hospital staff, and advanced medical support equipment not routinely available in other areas of the hospital. Although admission to the ICU does not necessarily mean a patient must be treated at MGH, the high acuity of intensive care patients undoubtedly increases the probability that they require specialized services during their treatment. The possible values for the ICU Status qualifier are "Non-ICU Patient" and "ICU Patient," with the former being more-highly correlated with avoidable admissions.

4.3.1.2 Medical Service

The capacity state of each medical service is a vital consideration when determining where MGH should focus its efforts toward reducing avoidable admissions. Since General Medicine is among the hospital's largest and most-heavily-utilized services, Medicine patients generally warrant greater scrutiny than those treated in other areas of the hospital. The possible values for the Medical Service qualifier are "Medicine Patient" and "Non-Medicine Patient," with the former representing a higher priority in terms of reducing avoidable admissions.

4.3.1.3 Transfer Type

As mentioned earlier, there are two types of facility-to-ED transfers: those originating from other hospital ED's (termed *ED-to-ED transfers*), and those arriving from psychiatric hospitals, rehabilitation clinics, or SNF's (termed *non-acute transfers*). Non-acute facilities clearly constitute a lower level of care, while other ED's provide equivalent care in all but the most severe circumstances. This is a critical distinction because the level of care associated with a transferring facility plays a key role in determining the interventions available for each patient.

To elaborate, EMTALA (detailed in Section 3.2.1) dictates that hospitals with specialized capabilities or facilities may not refuse a transfer patient if: i) they have the capacity to treat the patient, and ii) their capabilities exceed those of the referring hospital. The implication is that while MGH could refuse an ED-to-ED transfer that poses an avoidable admission risk, it could not refuse a non-acute transfer that poses the same risk. Instead, the hospital would need to consider other strategies, such as deploying additional resources to community hospitals or better leveraging technologies like telemedicine.[xii]

Since our analysis aims to inform the selection and implementation of interventions, it makes sense to parse avoidable admission candidates according to the interventions available to each type of patient. The possible values for the Transfer Type qualifier are "ED-to-ED Transfer" and "Non-Acute Transfer," with each permitting a unique set of potential interventions.

4.3.1.4 Medicare Severity-Diagnosis Related Group (MS-DRG) Classification

A Medicare Severity-Diagnosis Related Group (MS-DRG) is a coding system developed by the Centers for Medicare and Medicaid Services (CMS) to facilitate the payment of services related to a patient's hospital stay.[53] Because each of the approximately 750 possible MS-DRG's is defined by a set of patient attributes (including principal diagnosis, secondary diagnoses, procedures, and discharge status), the MS-DRG directly indicates acuity without requiring a physician to manually review a patient's medical file.

Recognizing this capability, we leverage the MS-DRG to classify each patient as one of three acuity levels: secondary, high-end secondary, and tertiary. The secondary classification indicates lower-acuity patients who can generally be properly treated in any community hospital, while the high-end secondary and tertiary designations imply patients whose treatment requires more-specialized care and resources.

[xii] Telemedicine involves the use of telecommunications technology to diagnose and treat patients remotely.

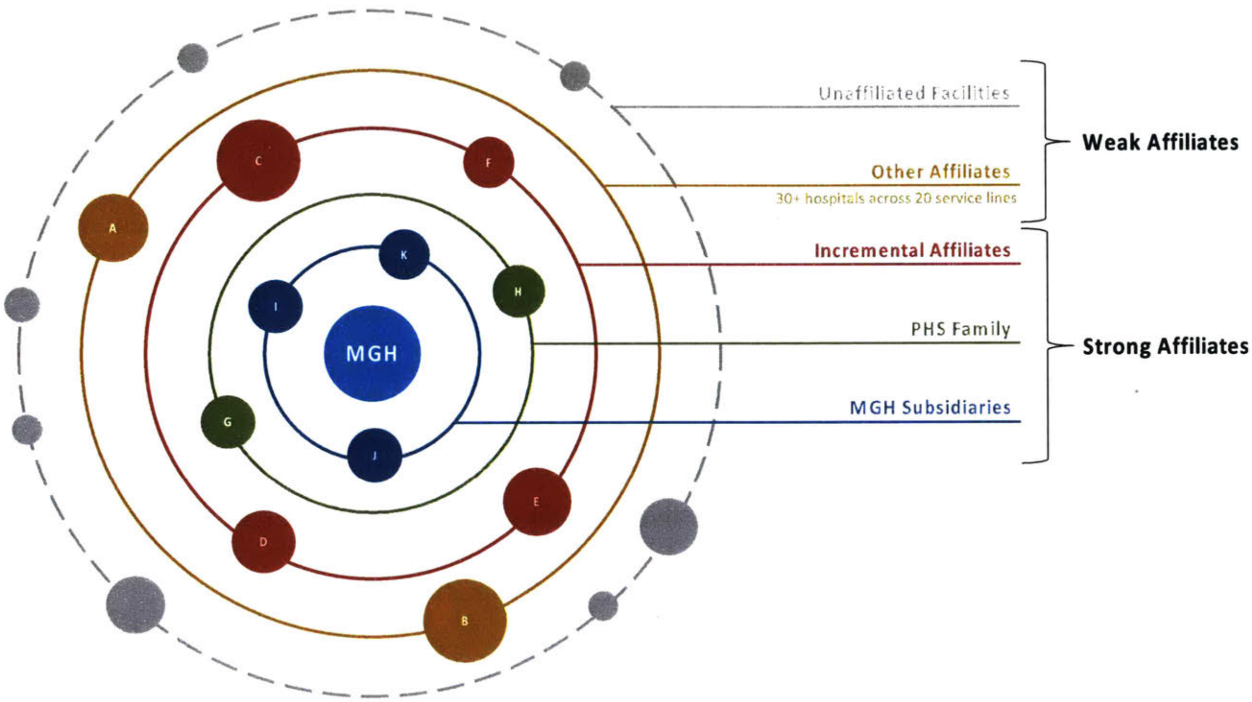
Since acuity is fundamental to the assessment of avoidable admissions, this methodology can be applied effectively as a patient qualifier. The logic here is straightforward: since MGH is a tertiary Academic Medical Center, if its capacity is used to treat secondary patients who could be effectively treated in other hospitals, it could be later forced to turn away tertiary patients whose conditions cannot be adequately treated elsewhere. The possible values for the MS-DRG Classification qualifier are "Secondary MS-DRG" and "High-End Secondary/Tertiary MS-DRG," with the former signaling patients who are less likely to require specialized resources during their treatment.

4.3.1.5 Facility Affiliation

As discussed in Section 4.2.3, the Network Development Relationship Database assigns each partner facility to one of five tiers reflecting the strength of the facility's affiliation to MGH. Figure 4-2 depicts these five tiers as progressively larger rings circling MGH at the center. Listed in order of priority, the tiers are labeled: i) MGH Subsidiaries, ii) PHS (Partners HealthCare System) Family, iii) Incremental Affiliates, iv) Other Affiliates, and v) Unaffiliated Facilities. The solid spheres linked to each ring represent example partner facilities, with their size and distance from the center indicating the strength of the relationship to MGH. On the far right, each tier is further identified as either a strong or weak affiliate, as determined by the Task Force.[xiii]

[xiii] These designations refer to the nature of the partnership with MGH, not the treatment capabilities of the facility.

Figure 4-2: Relationship Tiers & Affiliations



* Figure is adapted from a Network Development presentation. Facility names are anonymized to protect confidential information.

Holding all other factors constant, the stronger the affiliation between MGH and a transfer facility, the less scrutiny a secondary transfer request merits. Even if there is some indication the patient could ultimately become an avoidable admission, refusing the transfer could violate the terms of an existing partner agreement or simply damage a relationship that is in the best interest of both parties. The possible values for the Facility Affiliation qualifier are "Weak Affiliate" and "Strong Affiliate," with the former requiring closer attention when investigating avoidable admissions.

4.3.1.6 Primary Care Physician (PCP) Affiliation

Affiliations also exist between MGH and certain Primary Care Physicians (PCP's). Since PCP's are familiar with their patients' medical histories and other factors relevant to care, there can be significant value in having them manage treatment during and after a medical emergency. Patients may also insist that they be treated in their "home" hospital to have better access to family, friends, or other important support structures. All these factors provide added justification to accept a transfer request that might not otherwise seem necessary. The possible values for the PCP Affiliation qualifier are "Non-MGH PCP" and "MGH PCP," with the former requiring closer scrutiny with respect to avoidable admissions.

4.3.2 Avoidable Admission Profiles

The six binary patient qualifiers described in Section 4.3.1 can be combined in different configurations to form two distinct patient profiles. While each profile represents potentially avoidable admissions, the two are distinguished by the strategies that can be employed against them. Profile #1 represents transfers who may be appropriate to refuse, while Profile #2 captures patients who could potentially be avoided by deploying additional resources to community hospitals. Table 4-1 lists the specific patient qualifiers assigned to each profile and highlights how the two profiles differ from one another.

Table 4-1: Patient Qualifiers by Avoidable Admission Profile

Profile #1 Could potentially be avoided by refusing transfer	Profile #2 Could potentially be avoided by deploying additional hospital resources
Non-ICU Patients	Non-ICU Patients
Medicine Patients	Medicine Patients
ED-to-ED Transfers	Non-Acute Transfers
Secondary MS-DRGs	Secondary MS-DRGs
From Weak Affiliates	From Strong Affiliates
With Non-MGH PCPs	With Non-MGH PCPs

With respect to Profile #1, all but one of the qualifiers are included because they identify patients who are more-closely associated with avoidable admissions. The one exception is the ED-to-ED Transfer qualifier, which instead limits the interventions available with respect to the patients identified. In this specific case, since ED-to-ED patients are not transferring from a lower level of care, MGH can potentially refuse their transfer requests.

By switching the ED-to-ED Transfer qualifier to its Non-Acute counterpart, Profile #2 represents patients that cannot be refused for any reason. Instead, the most promising avenue to prevent these avoidable admissions is to elevate the level of resources available in community hospitals. To help focus these efforts, the Weak Affiliates qualifier is also switched. This change aims to capitalize on the fact that existing relationships provide the structures and lines of communication to facilitate an efficient exchange of resources between facilities.

4.4 Results

The following sections quantify the scope and trends associated with each avoidable admission profile before presenting facility-specific and patient-specific analyses designed to inform future interventions.

4.4.1 Profile #1: Candidates for Refusing Transfer Request

Figure 4-3 summarizes the results associated with Profile #1. On the left are the specific patient qualifiers utilized in the analysis. Note that they are arranged in the shape of a funnel to symbolize that each qualifier is applied to the output of its predecessor, progressively narrowing the focus population.

Figure 4-3: Profile #1 Results

	Avg Beds Per Day	
Patient Qualifiers Used to Identify Potentially Avoidable Admissions	**FY15**	**↑ from FY14**
All Facility-to-ED Transfer Admits	121	+13
Non-ICU Patients	87	+12
Medicine Patients	48	+10
ED-to-ED Transfers	30	+6
Secondary MS DRGs	20	+3
From Weak Affiliates	13	+2
With Non-MGH PCPs	11	+2
% of General Medicine Capacity	**5%**	**0.9%**

[1] Data Sources: EPSi & EDIS, Dates: FY14–15, Included Populations: Inpatients, Transfers, Adults (18+ Years Old)

[2] Average Beds Per Day was obtained by summing total annual bed-days for each qualifier and dividing by 365 days per year

To the right of the funnel are the average beds per day occupied by the patients associated with each layer of the profile, as well as the increase in bed-days that those patients generated over the previous year. Directing our attention to the bottom of the funnel, we see that these patients occupy between 11 and 20 beds per day, depending upon the level at which MGH chooses to engage the issue (per FY15 data). Furthermore, the growth associated with this patient population accounts for an average of two to three more beds daily than in FY14. Considering that General Medicine was already at capacity in FY14, the growth contributed by avoidable admission candidates among transfer patients is of immediate concern.

The last row of the figure translates these numbers to a percentage of the hospital's overall General Medicine capacity. Immediately striking is the fact that, for this Patient Profile alone, suspects for avoidable admission represent five percent of all General Medicine beds available. Additionally, the increase over 2014 is equivalent to almost one percent of the total beds available.[xiv]

4.4.2 Profile #2: Candidates for Deploying Additional Hospital Resources

Figure 4-4 summarizes the results associated with Profile #2. Again, the funnel on the left lists the specific patient qualifiers included in the analysis. As mentioned before, only two changes are made to those listed in the previous analysis. The first switches ED-to-ED Transfers to Non-Acute Transfers. This means patients associated with this profile cannot be refused, even if the other qualifiers suggest they are strong candidates for avoidable admission. Because the

[xiv] These calculations assume a total of 230 Medicine beds, as reported by the hospital's Admitting Department.

remaining interventions require close coordination with transferring facilities, the Weak Affiliates qualifier is also converted to Strong Affiliates.

Figure 4-4: Profile #2 Results

Patient Qualifiers Used to Identify Potentially Avoidable Admissions	Avg Beds Per Day FY15	 ↑ from FY14
All Facility-to-ED Transfer Admits	121	+13
Non-ICU Patients	87	+12
Medicine Patients	48	+10
Non-Acute Transfers	17	+4
Secondary MS DRGs	13	+4
From Strong Affiliates	4	+1
With Non-MGH PCPs	2	+1
% of General Medicine Capacity	0.9%	0.4%

Although smaller in scale than those of Profile #1, the results for Profile #2 are nonetheless substantial. Specifically, we see that on average these patients consume between two and thirteen beds per day and contribute an increase in demand of between one and four beds per day over FY14. Again, the range reported here affords the hospital some latitude in how it addresses avoidable admissions. Converting these figures to percentages reveals that patients associated with Profile #2 occupy 0.9 percent of the hospital's total General Medicine capacity, almost half of which can be attributed to an increase over the previous year.

Combining these results with those from Patient Profile #1, the analysis suggests that on any given day, almost six percent of the hospital's General Medicine capacity is expended by transfer admissions who are likely avoidable. Moreover, the growth associated with these patients in a single year is equivalent to 1.3 percent of all available General Medicine bed capacity. For a system that typically experiences utilization rates of between 95 and 100 percent, these figures are especially significant. Even if we discount half of the result due to a lack of precision in the methodology, the scale is still large enough to inspire serious concern regarding the prevalence of avoidable admissions among the focus population.

4.4.3 Facility-Specific Analysis

Considering the enormous impact of avoidable admissions among facility-to-ED transfers, it makes sense to perform a deeper dive by analyzing individual transfer facilities. This not only provides the hospital with greater insight regarding the problem, but also helps guide interventions by enabling the hospital to focus on the specific facilities that are most contributing to the problem. To perform this additional analysis, we first calculate the total bed-days generated by suspected avoidable admissions from each facility. To distinguish avoidable admission candidates in this context, we choose to apply the first four qualifiers of Profile #1. These include ED-to-ED transfers who are admitted to General Medicine with a secondary MS-DRG, while excluding ICU, Pediatric, and expired patients. Although an argument could be made for choosing other combinations of patient qualifiers, this sequence yields patients who have a large impact without being excessively restrictive.

After applying these qualifiers, we select the fifteen facilities whose patients generated the largest number of potentially avoidable bed-days at MGH. Choosing the top fifteen facilities enables the hospital to focus on a manageable group while at the same time prioritizing those that contribute most to avoidable bed-days. Finally, we incorporate other relevant facility details, including relationship tier, average length of stay, percent of patients with an MGH PCP, and percent of patients covered by either Medicare or Medicaid (also referred to as GP, or Government Payer). This additional information provides the context required to interpret each facility's results. Table 4-2 lists the facilities that emerge from this analysis in descending order according to the number of bed-days in FY15.

Table 4-2: Bed-Days by Facility (ED-to-ED Medicine Patients with Secondary MS-DRG's)

	Facility	Relationship Tier	GP[1] %	MGH PCP[2] %	Avg LOS[3] (Days)	FY15 Bed Days	% of Facility
1	A	MGH	69%	3%	6.1	573	74%
2	B	PHS	69%	11%	6.7	501	80%
3	C	Other	74%	23%	6.6	373	61%
4	D	Unaffiliated	60%	12%	6.7	361	81%
5	E	PHS	73%	15%	9.8	309	66%
6	F	ED	72%	21%	6.5	297	74%
7	G	MGH	60%	4%	4.7	268	83%
8	H	ED	71%	31%	9.7	251	55%
9	I	Incremental	51%	6%	10.4	241	55%
10	J	Other	68%	22%	7.8	211	57%
11	K	Other	78%	22%	6.6	183	84%
12	L	Other	67%	20%	10	166	49%
13	M	Other	82%	13%	8.7	148	59%
14	N	Unaffiliated	84%	19%	6.2	139	64%
15	O	ED	67%	25%	7.4	134	63%
	Top 15	-	-	-	-	4,155	37%
	Weak Affiliates in Top 15	-	-	-	-	2,263	20%
	All ED-to-ED Med Pts	-	-	-	-	7,213	65%

[1] GP = Government Payer, meaning the percentage of patients whose care is covered by either Medicare or Medicaid
[2] PCP = Primary Care Provider
[3] LOS = Length of Stay
[4] Facility names are anonymized to protect confidential information.

The core value of Table 4-2 is that it provides increased transparency regarding the impact that specific relationships have on the patient mix at MGH. That said, it is important to realize this information cannot be viewed in a vacuum. For instance, an especially-high percentage of Medicare or Medicaid transfers could have many possible explanations, including that a facility is intentionally dumping non-revenue generating patients onto MGH or that its transfer pool simply reflects the natural patient demographics of the community it serves. One explanation is nefarious while the other is benign, but it is not clear which is accurate based on this data alone. For this reason, the tool should be used to initiate cooperative dialogues with partner facilities as opposed to serving as an enforcement mechanism.

Ironically, many of the institutions responsible for transferring large numbers of avoidable admission candidates simultaneously suffer from low occupancy rates in their own facilities.[xv] Considering the detrimental impact that low occupancy can have on a hospital's profitability, this insight is certainly counterintuitive and suggests that the results in Table 4-1 are more a sign of limited awareness than any ill intent on the part of other organizations. By exposing this phenomenon and assisting other facilities to better understand the factors driving it (whether it be proximity to the patient's home, the desire to be treated by a familiar doctor, or attitudes concerning hospital reputation), the analysis ultimately reveals win-win opportunities for both MGH and its partners.

Another significant takeaway from Table 4-1 is that patients originating from just the eight weak affiliates included in the top 15 account for 20 percent of the total bed-days occupied by ED-to-ED Medicine patients. This means that MGH can engage a very small number of facilities and still make substantial headway in reducing the number of bed-days associated with avoidable admissions from within the transfer population.

[xv] This information was relayed to the author by MGH administrators who are privy to reporting on other Partners institutions.

4.4.4 Patient-Specific Analysis

Another key question that arises from the analysis presented in Section 4.3.2 concerns which specific diagnoses are linked to the patients identified as avoidable admission candidates. Again, this information can help guide future interventions by focusing the hospital's efforts on the diagnoses that most contribute to avoidable bed-days. To answer this question, we create a frequency distribution of secondary MS-DRG's and isolate the top 15 most frequent diagnoses, again focusing on ED-to-ED transfers who are admitted to General Medicine. Table 4-3 lists the results of this analysis.

Table 4-3: Secondary MS-DRG Frequency Distribution (ED-to-ED Medicine Patients)

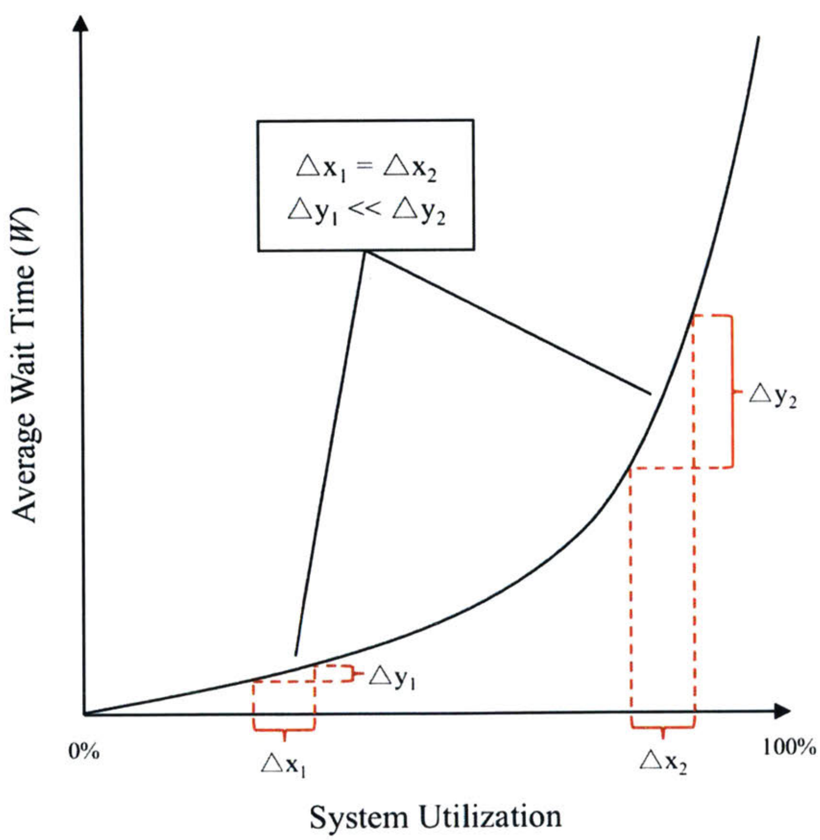
	DRG	%
1	G.I. HEMORRHAGE W CC	3%
2	ESOPHAGITIS, GASTROENT MISC DIGEST DIS W/O MCC	2%
3	MEDICAL BACK PROBLEMS W/O MCC	2%
4	PERC CARDIOVASC PROC W DRUG-ELUTING STENT W/O MCC	2%
5	CIRCULATORY DISORDERS EXCEPT AMI, W CARD CATH W/O	2%
6	POISONING TOXIC EFFECTS OF DRUGS W/O MCC	2%
7	RENAL FAILURE W CC	2%
8	ALCOHOL/DRUG ABUSE OR DEPEND W/O REHAB THER W/O MC	2%
9	CELLULITIS W/O MCC	2%
10	HEART FAILURE SHOCK W MCC	2%
11	OTH DIGESTIVE SYS DX W CC	2%
12	ACUTE MYOCARDIAL INFARCTION, DISCHARGED ALIVE W CC	1%
13	ACUTE MYOCARDIAL INFARCTION, DISCHARGED ALIVE W MC	1%
14	DIS OF LIVER EXCPT MALIG,CIRR,ALC HEPA W MCC	1%
15	OTH CIRCULATORY SYS DX W CC	1%

Immediately, we notice that several MS-DRG's included in this list correspond to those anecdotally reported by physicians to be associated with avoidable admissions, including back pain and conditions linked to drug and alcohol abuse. Therefore, this analysis provides the first data-based confirmation of those perceptions. It also points to other conditions that could potentially serve as targets for future interventions.

4.5 Key Findings

Figure 4-5 depicts the classic, reciprocal relationship that exists between system utilization and average patient wait time according to queuing theory.[54]

Figure 4-5: System Utilization vs. Patient Wait Time Curve*



* For MGH specifically, $\Delta x_2 = 1\%$ while $\Delta y_2 = 20\%$

As the figure shows, for systems that are not highly-utilized, a slight increase in utilization (Δx_1) yields only a slight increase in patient wait time (Δy_1). For highly-utilized systems like MGH, however, even a slight increase in demand (Δx_2) can cause a dramatic spike in corresponding wait times (Δy_2). Underlying this phenomenon is the intrinsic variability of healthcare processes.

This concept helps explain the symptoms that emerged in 2015. It also suggests that the seemingly small one percent increase in demand linked to avoidable admissions among facility-to-ED transfers could alone account for the disproportionate 20 percent increase in patient wait times and 164 percent spike in Code Help and Capacity Disaster activations experienced over the previous year. On a positive note, this also implies that even minor reductions in the number of avoidable admissions among the study's focus population could have an equally dramatic impact in terms of alleviating the hospital's current capacity issues.

4.6 Recommendations

The prevalence of avoidable admission candidates among facility-to-ED transfers suggests there are opportunities to improve the way MGH interacts with the transfer patient population. This includes enhancing how the ED evaluates incoming transfer requests, how it handles patients within the department, and how it engages with other facilities to attract complex transfers who are truly appropriate for MGH. With that in mind, the following sections detail the main recommendations that spring from the chapter's earlier analysis.

4.6.1 Standardize the Transfer Request Protocol

The current process to submit a transfer request is inconsistent and difficult to navigate. For one, there are numerous methods of making a request, including calling the ED access nurse, the charge nurse for a specific inpatient floor, or a hospital physician who may already be familiar with the patient, as well as electronically submitting a request via the hospital's Customer Relationship Management System. The contact method, specific hospital staff member involved, desired destination of the patient, and even time of day can all impact the process and likelihood that a transfer will be accepted. Apart from being a source of frustration for other facilities, this also hinders MGH's ability to effectively manage the transfer process at a systems level. To remedy this, the transfer request protocol should be standardized across the hospital.

4.6.2 Refine Department Protocols for Evaluating Transfer Requests

While the Access Program Transfer Algorithm certainly *appears* stringent (see Figure 3-4), data from the past three years reveals that the department typically accepts close to 97 percent of all transfer requests received.[35] This, combined with the substantial number of inpatient bed-days consumed by avoidable admissions from within the transfer population, suggests that further optimization is both possible and necessary.

One serious flaw is the blunt and maladaptive nature of the Transfer Algorithm with respect to assessing capacity within the hospital. When evaluating an inpatient floor, for example, the service is either full at that instant in time, in which case the transfer is refused, or it is not, in which case the transfer is accepted. Although the five ED capacity levels (summarized in Table 3-2) offer a slightly more granular measure of capacity for that department, the criterion to accept or refuse a transfer based on the ED's service level is likewise binary: either the department has reached Code Help, and the transfer is refused, or it has not, and the transfer is accepted. In both cases, the decision relies entirely on a discrete snapshot of the hospital's capacity state with no attempt to anticipate future capacity demands.

This near-sighted approach creates a harmful dynamic in which the hospital may be motivated to accept non-tertiary patients during temporary lulls in demand, only to later be forced to refuse tertiary patients due to a lack of space. In an environment as complex and dynamic as MGH, this brand of reactive methodology lacks the rigor needed to be effective. Therefore, a more proactive and adaptive approach is required.

To achieve this, the ED should establish a multidisciplinary team that more systematically assesses the appropriateness of transfer requests. At a minimum, the team should include dedicated physicians, who can more rigorously assess the clinical needs of potential transfers, and Admitting personnel, who have a more nuanced appreciation for the capacity state of various medical services throughout the day. Together, the team should create enhanced selection criteria that incorporate more stringent clinical oversight and a forward-looking view of the capacity state of the hospital. This will require the use of predictive analytics to anticipate future demand by leveraging historical trends and the expected LOS for patients entering MGH.

4.6.3 Continue the General Medicine Divert Policy

Near the beginning of this project, the ED began testing a General Medicine Divert Policy that prohibits the Access Program from accepting General Medicine transfers once the number of ED boarders reaches ten or more patients. While this strategy does not remotely approach the refined and proactive one described in the previous recommendation, it does make sense as a stop gap until the hospital is able to develop the capabilities to implement a more sophisticated solution. At the very least, it reduces the likelihood that MGH will be forced to refuse tertiary Medicine patients because it previously accepted an excessive number of secondary ones. For this reason, the Medicine Divert Policy should be maintained. The threshold could also be decreased to five patients to further reduce the probability of later refusing tertiary patients.

4.6.4 Engage with Strong Affiliates to Refine Partner Agreements

Although the partner agreements that MGH maintains with other institutions are designed to attract only complex patients, it is apparent from the analysis in Section 4.3.2 that many relationships have the unintended consequence of drawing an abundance of secondary patients as well. This implies that MGH would benefit from reviewing its existing agreements, in coordination with Strong Affiliates, to determine what changes might reduce this side effect.

This recommendation is essentially the strategic complement to the first recommendation. Rather than improving the transfer evaluation criteria to reduce avoidable admissions at an operational level, refining the transfer agreements themselves strikes at the root of the problem. This has the potential to create an environment in which inappropriate transfer requests are less likely to be directed to MGH in the first place.

4.6.5 Expand the Homecare Pilot Program

The Home Care Program, an initiative that the ED piloted concurrently with this project, enlists Case Managers to aggressively seek out ED patients who could be responsibly discharged with expanded home care services. Since early indicators show strong potential for preventing admissions using this mechanism, the hospital should continue to develop the program with the intent of making it a permanent fixture within the ED. If the concept continues to prove effective, it would provide a prudent second layer of protection to accompany the refined evaluation protocols described earlier.

4.6.6 Coordinate with Community Hospitals to Expand In-Situ Capabilities

One last recommendation to reduce the number of avoidable bed-days generated by transfer patients is to assist targeted community hospitals in expanding their in-situ capabilities. This could involve incorporating more tele-health assets, growing on-site consult offerings, or establishing new services altogether. The logic here is that the more equipped these hospitals are to treat secondary patients, the less motivated they will be to transfer them for offsite care. Through its Network Development team, MGH already works extensively with other hospitals to build external capabilities, so this in no way represents a stretch for the hospital. It is also reasonable to assume community hospitals will be highly receptive to receiving assistance from MGH since both their capabilities and reputation stand to benefit from the exchange.

Chapter 5

Analysis of Short-Stay Admissions

This portion of the analysis explores the second of the two hypotheses presented in Chapter 1, namely that avoidable admissions strongly correlate with patients who receive unusually low levels of physician care while they are admitted to MGH. To test this theory, hospital order data is used as a proxy for the level of care patients receive. Although it is intuitive that orders (which reflect the specific medications, tests, and services that physicians request on behalf of patients) could be used to measure a patient's level of care, the concept has not been previously validated using data from MGH. Thus, a portion of this chapter is dedicated to establishing a compelling relationship between hospital order data and avoidable admissions. A scoring methodology is then developed in collaboration with hospital physicians to automatically identify avoidable admission candidates.

5.1 Data Sources and Integration

The analysis of short-stay admissions utilizes information from three hospital data sources: i) EDIS, ii) EPSi, and iii) Physician Order Entry (POE). Since EDIS and EPSi are already detailed in Chapter 4, only POE is further discussed here.

5.1.1 Physician Order Entry (POE)

In general, Physician Order Entry (POE) is any application that enables medical providers to digitally enter instructions (or orders) for the treatment of patients. Once entered, orders are transmitted over a computer network to the medical staff or departments responsible for completing them (e.g., pharmacy, laboratory, radiology).[55] POE replaces more traditional methods of communicating medical orders, including written (delivered by hand or via fax) and verbal (delivered in person or via telephone).[56]

From this perspective alone, POE improves patient safety by ensuring that orders are legible. But even greater protection is achieved through the integration of clinical decision support (CDS) systems that provide real-time feedback about a wide range of diagnostic- and treatment-related information. Governed by an extensive set of electronic rules, CDS can alert providers to a variety of potential errors, including unsafe drug interactions, patient allergies to prescribed medications, medication contraindications,[xvi] and renal- and weight-based dosing discrepancies.[56]

Most POE systems allow providers to electronically specify a variety of different order types, including medication, laboratory, and procedure orders. In fact, this project utilizes two separate POE datasets that incorporate fourteen different order types. The first set, which was obtained toward the beginning of the project, contains general information, such as the time, location, and type of order. The second set, which was obtained many months later, provides detailed information regarding each of the fourteen order types. In the case of medication orders,

[xvi] Contraindications are situations in which a drug, procedure, or surgery should not be used because it may be harmful to the patient. For example, Isotretinoin (a drug used to treat acne) is contraindicated in pregnancy due to the risk of birth defects.

for example, the additional data table lists the specific medications, doses, and frequencies associated with each order. Altogether, the POE data supplied for this study includes nearly 1.2 million orders stemming from over 9,700 patient accounts, all of which occurred during fiscal year 2015. 42 features are provided for each order.

The unsupervised and supervised learning methods described in this chapter are performed using the generalized data. The more detailed data is then used to develop a scoring methodology that identifies avoidable admission candidates without requiring manual case review. This approach is developed in close coordination with hospital physicians.

5.1.2 Data Integration

For the unsupervised and supervised learning methods, which utilize the generalized POE data, records from POE and EDIS are merged using the *Encounter ID* field. The resulting dataset is then combined with EPSi data using the *EPSi Patient Account* field. This process yields 6,045 separate patient encounters that all occurred during fiscal year 2015.

For the scoring method, which utilizes the detailed POE data received late in the project, the fourteen POE tables are first merged using the *Order ID* field. The POE, EDIS, and EPSi sources are then combined using the *EPSI Patient Account* field. Combining the data in this way produces 9,707 patient encounters. Ideally, both analyses would be executed using the second, more-detailed dataset. However, due to the timing of each data pull, further exploration of the detailed POE data must be performed in subsequent studies.

5.2 Focus Population

As in the previous chapter, it is helpful to identify the specific patient population included in the analysis. This group, labeled *short-stay admissions*, consists of all patients who meet two general criteria: first, that they were admitted from the ED to one of the hospital's inpatient floors during fiscal year 2015, and second, that their length of stay (LOS) did not exceed four days.[xvii]

Limiting the study to patients with a LOS of four days or less serves three main functions. First, it focuses the analysis on admissions that are more likely to be avoidable. The rationale is that patients who stay longer than four days tend to have more serious conditions that require specialized care. Next, it reduces the massive volume of data required from MGH, which is necessary given existing time and resource constraints. Lastly, it prevents sensitive patient data from being unnecessarily jeopardized, in adherence with the hospital's data security protocols. Since the methodology developed in this chapter is intended to be applied only to similar populations, there should be no concern that limiting the focus population in this way will bias the results of future analyses.

It is also important to note that several patient groups are specifically excluded from the analysis. For example, anyone under the age of 18 is omitted since the unique anatomy and physiology of children makes their care needs especially extensive at times. Also excluded are patients who expired during their visit since death implies their admissions were probably

[xvii] The four-day threshold was chosen based on recommendations from the members of Task Force 1.

necessary. Finally, patients admitted to MGH without first being routed through the hospital's ED are considered beyond the scope of this study.

5.3 Unsupervised Learning Method (*K*-Means Clustering)

One challenging aspect of investigating avoidable admissions is the lack of any large set of patients who have been identified, even retrospectively, as avoidable. This is true because the current method of determining if an admission is avoidable (i.e., manual case review by a physician) is both labor intensive and time consuming. This lack of labeled data makes unsupervised learning a logical first step in analyzing the order data provided.[57] The most common unsupervised learning method is cluster analysis, which is used to explore data by grouping observations (in our case, patients) using a measure of similarity defined by metrics such as Euclidean or probabilistic distance.[58]

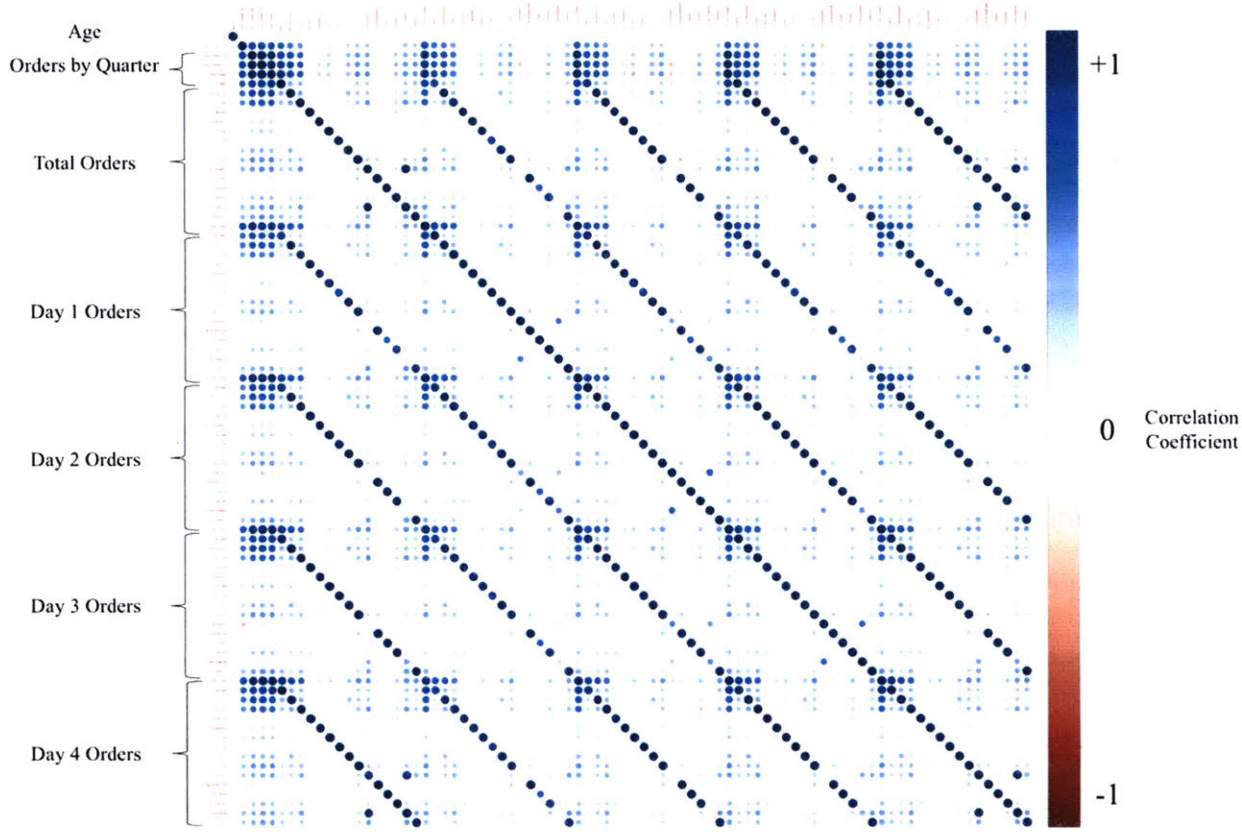
5.3.1 Methodology

We choose to apply *k*-means clustering to the generalized POE data (meaning the set that does not contain specific details about each order) with the expectation that grouping patients based on features anecdotally associated with avoidable admissions (e.g., LOS, age, order frequency) could yield insights regarding other avoidable admission qualities. A hypothetical example of this would be if one of the clusters formed by *k*-means exhibited features currently associated with avoidable admissions, as well as an especially high concentration of a specific diagnosis, such as cellulitis. In this hypothetical scenario, better resources or methods for managing cellulitis patients could be targeted as a means of reducing avoidable admissions. Further rationale is that patients with similar clinical orders may also have similar classifications in terms of being avoidable or unavoidable.

5.3.1.1 Feature Selection and Scaling

The first step in applying *k*-means is selecting features that could be helpful in identifying avoidable admissions. Dozens of attributes are initially derived from the generalized POE data and evaluated for redundancy using the correlation plot that appears in Figure 5-1. Due to space constraints, the specific attributes listed in red along the left and top sides are not fully legible, but they include patient age, total quantity of orders by quarter of the stay, and total quantity of orders and quantity of orders by day, which are both aggregated separately by order type (e.g., medication, blood, radiology, etc.). Plots are generated for several different attribute combinations before choosing which ones to use for clustering.

Figure 5-1: Correlation Plot Showing Prevalent Redundancy Among Clustering Features



In the figure, dark blue circles indicate a +1 correlation between features, dark red circles a -1 correlation, and white circles a correlation of zero. Since the same features are listed along the horizontal and vertical axes, we expect to see dark blue circles running diagonally from the upper left corner to the bottom right corner of the chart. This simply indicates that identical attributes are perfectly correlated. The remaining dark blue circles, however, indicate redundant features, which would be harmful to include when implementing *k*-means since they effectively bias the model. After generating multiple correlation plots using various feature combinations, and upon further discussions with hospital staff, the sixteen features listed in Table 5-1 are selected for clustering.

Table 5-1: Clustering Features[xviii]

	Attribute	Description
1.	Age	Patient age in years
2.	LOS.Floor	Time duration on inpatient floor in hours
3.	Floor.Orders	Total number of orders received while assigned to an inpatient floor
4.	Rate.Floor.Med	Hourly rate of **medication** orders
5.	Rate.Floor.Pathology	Hourly rate of **pathology** orders
6.	Rate.Floor.Blood	Hourly rate of **blood** orders
7.	Rate.Floor.DiagProc	Hourly rate of **diagnostic process** orders
8.	Rate.Floor.Rad	Hourly rate of **radiology** orders
9.	Rate.Floor.IV	Hourly rate of **IV** orders
10.	Rate.Floor.Respiratory	Hourly rate of **respiratory** orders
11.	Rate.Floor.Dietary	Hourly rate of **dietary** orders
12.	Rate.Floor.Consult	Hourly rate of **consultation** orders
13.	D1.Dist.Floor	Percent of total orders received in **Day 1** of stay
14.	D2.Dist.Floor	Percent of total orders received in **Day 2** of stay
15.	D3.Dist.Floor	Percent of total orders received in **Day 3** of stay
16.	D4.Dist.Floor	Percent of total orders received in **Day 4** of stay

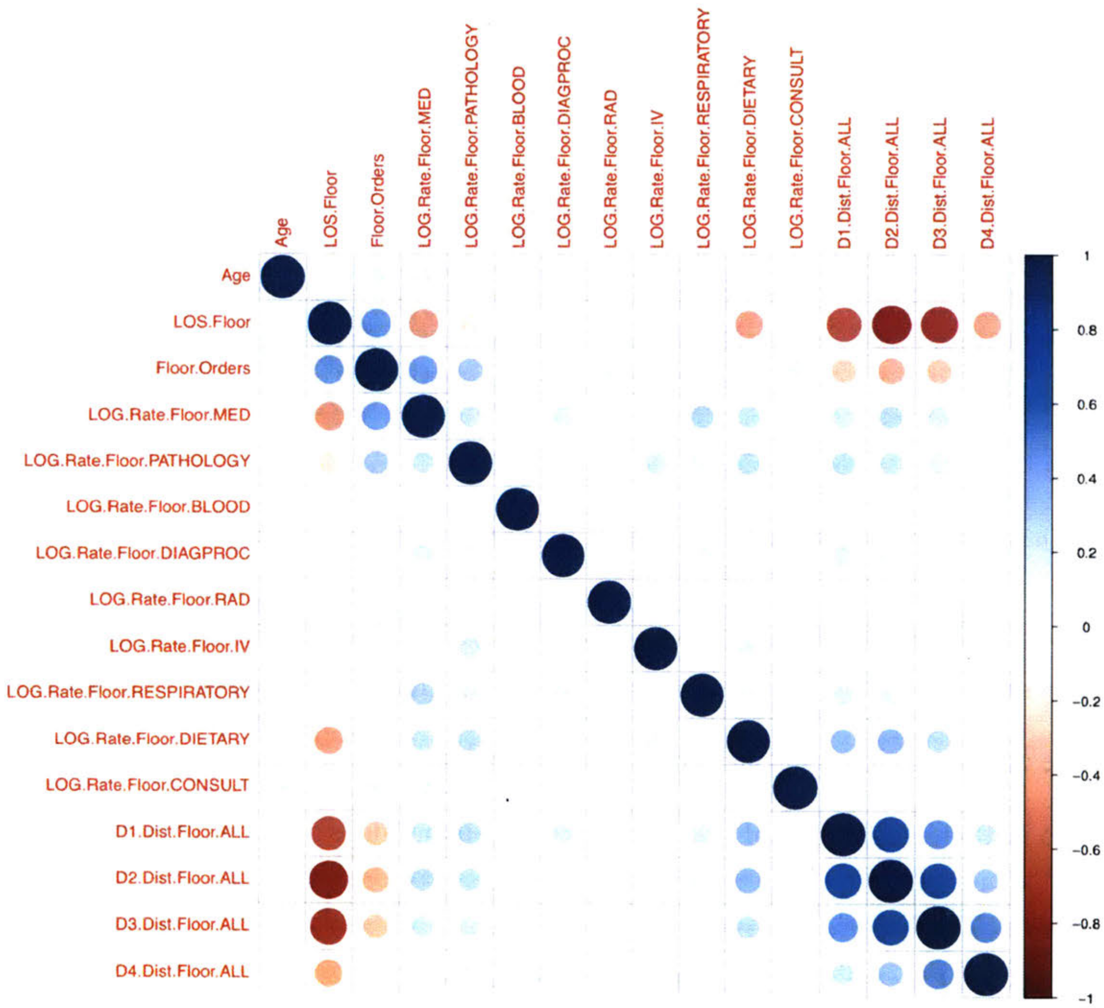
It is necessary to acknowledge that all attributes, including those selected here, have advantages and disadvantages. The percent of total orders received in Day 4, for instance, is a misleading metric for patients who remain in the hospital for only two days.[xix] Likewise, the hourly rate of diagnostic procedure orders is naturally lower for patients who stay four days as opposed to just one, regardless of how necessary their admissions. Recognizing that no attribute is perfect, the features in Table 5-1 are considered to strike a fair balance between their inherent strengths and weaknesses relative to other feature possibilities.

[xviii] The hourly rate of each order type is calculated by summing the total number of orders and dividing by the patient's LOS in hours. The daily distribution of floor orders is calculated by summing the total orders received during each day of the hospitalization and dividing by the total number of orders received over the entire LOS.

[xix] In this case, the feature is populated with zeros. We avoid assigning NAs since *k*-means functions best with continuous variables. In some cases, binary variables can be used by treating them as continuous, but this makes the results difficult to interpret since the cluster centroids will no longer have continuous values. Also, *k*-means should not be used with mixed data types because it relies on squared Euclidean distances to partition the data.[68] [69]

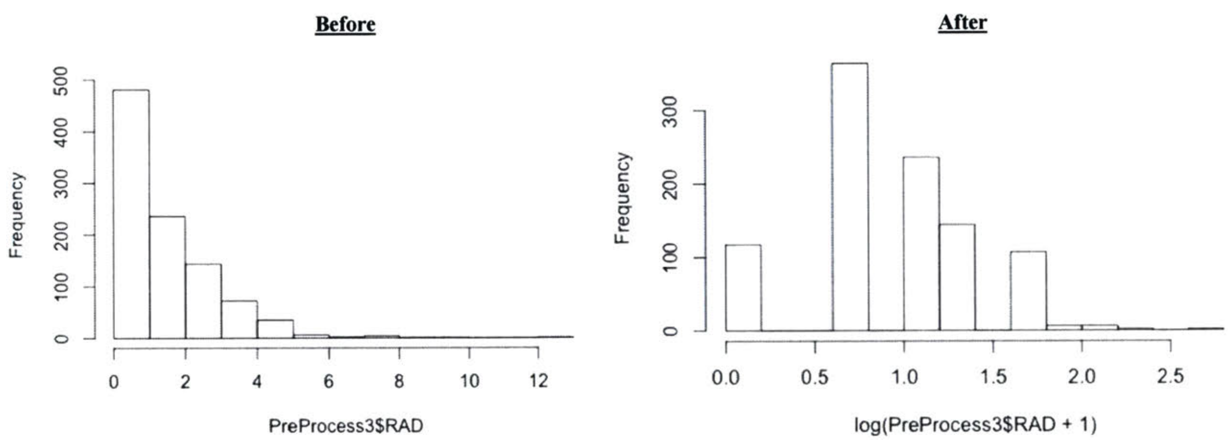
Again, a correlation plot is created to ensure that redundant features are minimized. Figure 5-2 confirms that redundancy is not prevalent among the selected attributes.

Figure 5-2: Correlation Plot Showing Limited Redundancy Among Clustering Features



With the clustering features selected and checked for redundancy, we generate histograms to determine if the distribution of each attribute is roughly normal. Substantial deviations from a bell-shaped distribution indicate the presence of outliers that can distort the clustering results. Three options are available when this occurs: i) outliers can be excluded entirely, ii) outliers can be capped to some maximum value, or iii) the feature can be logarithmically transformed. For this study, the log transform method is favored, although capping is also employed in limited cases. Figure 5-3 demonstrates the benefit of applying the log transform when appropriate. On the left, the histogram for the number of radiology orders is severely skewed, while on the right, it is more normally distributed.

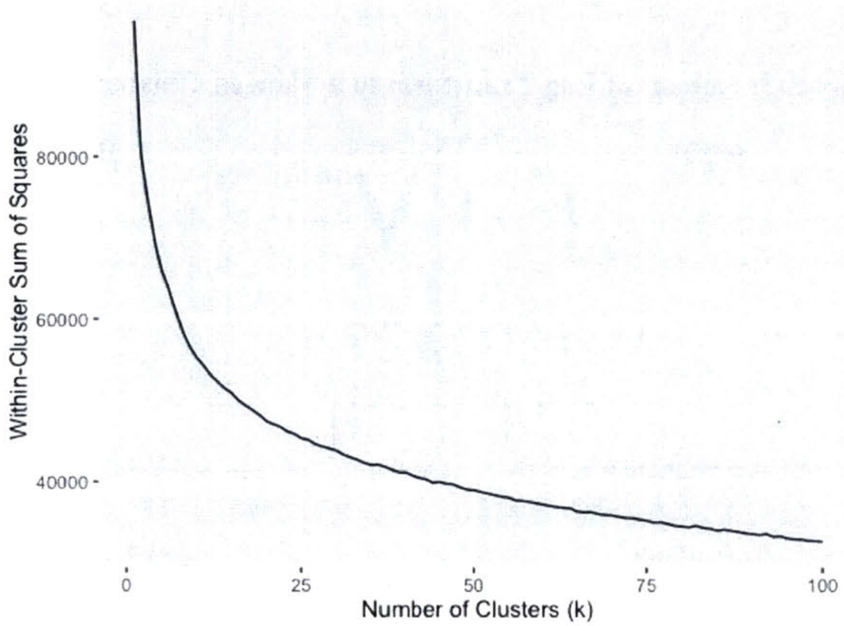
Figure 5-3: Impact of Log Transform to a Skewed Clustering Feature



5.3.1.2 Cluster Selection

Before running *k*-means, we must first determine the number of clusters, *k*, that we want the algorithm to generate. To inform this decision, we produce a scree plot to help visualize the tradeoffs associated with different *k* values. Specifically, the scree plot depicts the sum of squared differences between the feature values for each patient and the corresponding mean values for the cluster the patient is assigned to, given many different values for *k*. As illustrated in Figure 5-4, increasing the number of clusters reduces the sum of squared differences – rapidly at first, then with diminishing returns. At some point, however, generating more clusters also eliminates the value of clustering at all. Grouping 100 patients into 98 clusters, for instance, serves no practical purpose. That said, selecting a *k* that lies somewhere along the knee of the curve represents a sensible compromise between these two competing priorities.

Figure 5-4: Scree Plot Indicating Appropriate Number of Clusters, *k*



Referencing the scree plot, we see that the knee of the curve lies somewhere between eight and fifteen clusters. After experimenting with *k* values in this range, the team ultimately decided that eight clusters are most appropriate for this project. This is driven primarily by the perceived difficulty of interpreting results associated with higher *k* values.

5.3.2 Results

After implementing *k*-means, we review the centroids for each generated cluster across many different attributes. This includes those features applied to the clustering algorithm, such as patient age and LOS, as well as others that are potentially relevant to the analysis, such as the percentage of each cluster composed of frequent flyers.[xx] The goal here is to identify one or more clusters whose attributes convincingly resemble those of avoidable admissions. For instance, an intriguing cluster might contain a high concentration of elderly patients with short LOSs or high percentages of ACSCs and frequent fliers. Table 5-2 provides a sample of the centroids reported to give a better sense of the process used to assess the clustering results. Note that this table includes only a portion of the centroids evaluated. Also keep in mind, these are not unique patients, but unique hospitalization episodes, which could involve the same patient visiting the hospital numerous times.

[xx] Frequent flyers are individuals who repeatedly and excessively utilize ED and inpatient services as their primary source of medical care. Many of these patients visit the ED dozens of times annually, but the term generally includes anyone with ten or more visits per year.

Table 5-2: Sample of Reported Cluster Centroids

Cluster	Count	Bed Days	Avg LOS (Hours) ED	Avg LOS (Hours) Floor	Avg LOS (Hours) Total	Avg Age	ACS[1] %	CMS[2] %	FF[3] %	Level 1[4] %
1	555	961	4	38	42	65	18%	72%	16%	44%
2	852	1,973	4	51	56	66	26%	79%	28%	43%
3	356	951	4	60	64	62	6%	67%	29%	59%
4	933	3,719	5	91	96	67	29%	80%	31%	44%
5	284	1,308	5	106	111	65	25%	78%	32%	42%
6	836	1,802	5	47	52	53	12%	54%	18%	45%
7	1,312	4,102	5	71	75	61	22%	70%	24%	39%
8	917	3,154	5	78	83	62	22%	75%	31%	61%
Base	6,045	17,969	5	67	71	62	21%	72%	26%	46%

[1] Percent of cluster exhibiting ambulatory care-sensitive conditions, which would not require hospitalization if managed properly

[2] Percent of cluster composed of Medicare or Medicaid patients

[3] Percent of cluster composed of frequent flyers, or those who rely excessively on hospital services

[4] Percent of patients considered to be more urgent in nature (patients are coded as either Level 1 or 2)

In addition to reporting the percentage of patients within each cluster exhibiting ACSCs, we also examine the distribution of ACSCs across clusters. Table 5-3 illustrates these results. From this perspective, clusters 2, 4, 7, and 8 may be of interest seeing as they have higher percentages across all seven ACSCs relative to their counterparts.

Table 5-3: Distribution of ACSCs Across Clusters

ACSC	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Sum
Bacterial Pneumonia	7%	25%	1%	22%	5%	12%	14%	15%	100%
Cellulitis	2%	9%	4%	19%	3%	14%	39%	9%	100%
COPD	17%	21%	1%	25%	6%	2%	16%	12%	100%
Dehydration	11%	31%	6%	14%	0%	6%	17%	17%	100%
Diabetes	7%	11%	0%	11%	3%	23%	7%	39%	100%
Heart Failure	10%	35%	2%	25%	8%	2%	8%	10%	100%
UTI	3%	20%	2%	28%	8%	10%	18%	10%	100%

5.3.3 Key Findings

Even after running multiple scenarios by varying the clustering attributes and *k* values, the results are not exceedingly compelling. The criteria for this assessment is admittedly subjective. Even when a cluster centroid that is related to avoidable admissions exhibits a statistically significant difference from the base (i.e., the centroid for all patients prior to clustering), it does not automatically follow that the cluster includes mostly avoidable admissions. In this sense, the bar for this analysis to identify avoidable admission candidates is exceedingly high.

While the results of the unsupervised clustering are not as dramatic as we may have liked, there is at least one interesting insight that warrants further investigation. That is, the distribution of ACSCs across clusters indicate that some clusters contain higher concentrations of ACSCs relative to their peers. Review by physicians will help determine if this clustering of patients is helpful to identifying avoidable admissions.

5.4 Supervised Learning Methods (Random Forest and Logistic Regression)

In addition to the unsupervised learning approach, supervised methods are also explored. Specifically, we apply logistic regression and random forest to further investigate if orders can, in fact, provide any meaningful insights regarding avoidable admissions.

5.4.1 Methodology

In contrast to unsupervised learning, a requirement of the supervised approach is that a portion of the data be labeled as either avoidable or unavoidable prior to implementing the methodology. This is necessary because the algorithms must "train" on a labeled dataset before attempting to predict the response variable for an unlabeled one. Since our data is not labeled due to the excessive resources required to classify patients as avoidable, we must select a proxy instead.

The proxy chosen is known as an ambulatory care-sensitive condition (ACSC). ACSCs are medical conditions that can be avoided with timely and effective outpatient care,[59] such as adhering to diet restrictions or properly taking prescribed medications. While there is not universal agreement regarding the conditions that qualify, Table 5-3 captures the seven conditions most-commonly labeled as ACSCs in the literature reviewed for this study.[60 61 62 63 64] Before proceeding, any patient who exhibits one of these seven diagnoses as his or her primary diagnosis is labeled avoidable.

Table 5-3: Conditions Most-Commonly Labeled as ACSCs

Condition
1. Bacterial Pneumonia
2. Cellulitis
3. Chronic Obstructive Pulmonary Disorder (COPD)
4. Dehydration
5. Diabetes
6. Heart Failure
7. Urinary Tract Infection (UTI)

To be clear, ACSCs do not precisely match our concept of an avoidable admission because they focus on the frequency and quality of care received in the months leading up to hospitalization rather than the care resources actually demanded in the hospital. Nonetheless, there is qualified research linking ACSCs to patients who receive unusually low levels of hospital care. Ouslander et al., in a study of nursing home patients in Georgia, reports that 95 percent of the hospitalizations that physicians retrospectively classified as avoidable (using standards analogous to this study) were for ACSCs.[65] Furthermore, research conducted at MGH by Ticona et al. reveals a strong correlation between ACSCs and ED patients identified as candidates to be discharged with home care services rather than being admitted.[66] This research supports the decision to use ACSCs as a proxy for avoidable admissions.

After applying labels, the next step is to partition the data into testing and validation samples. This is accomplished using two methods. First, we perform random sampling to create a 40/60 split of the data. The smaller sample is used to train the methodology, while the larger one is used to test its effectiveness. Stratified sampling is then applied separately and the results are compared to determine which is the better sampling technique. Stratified sampling is expected to prevail since it ensures that the distribution of ACSCs within the two samples most closely resembles that of the original dataset.

With the dataset labeled and partitioned, we apply both random forest and logistic regression to see how well we can identify ACSCs, both individually and as a group. To be consistent, we use the same features employed in the previous analysis.

5.4.2 Results

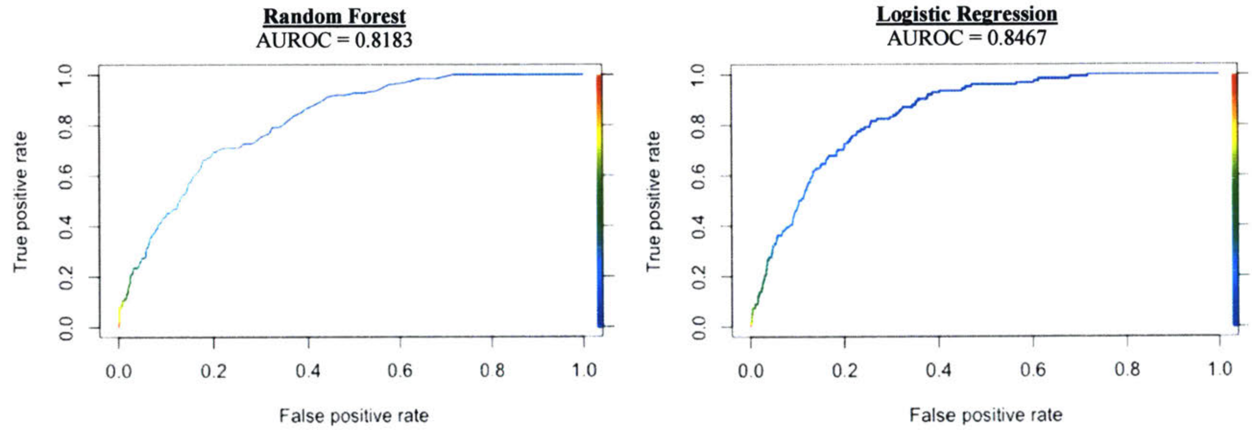
Because ACSCs represent a small fraction of the overall dataset (typically between two and six percent), simply reporting the accuracy of each model does not provide a fair measure of classification ability. We could achieve high accuracy, for instance, by simply labeling every patient unavoidable. By only considering the frequency of true positives, accuracy provides a misleading sense of model efficacy.

5.4.2.1 Area Under the Receiver Operating Characteristic Curve (AUROC)

To avoid this mistake, we instead leverage the receiver operating characteristic curve (ROC),[xxi] which incorporates the true positive and false positive rates for each model. The area under this curve (AUROC) provides a more useful performance metric, with a value of 0.5 indicating a series of random guesses and a value of 1.0 indicating a perfect model. Figure 5-5 displays example ROCs for identifying heart failure using both random forest, on the left, and logistic regression, on the right.

[xxi] In statistics, a ROC is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The curve is created by plotting the true positive rate against the false positive rate at various threshold settings.[72]

Figure 5-5: Receiver Operating Characteristic Curves (AUROCs) for Identifying Heart Failure



The AUROCs calculated using both random and stratified sampling are compiled in Table 5-4, with the highest value for each ACSC highlighted in red. The best AUROCs have an average value of 0.76, with a high of 0.85 and a low of 0.63. Interestingly, logistic regression outperforms random forest for all conditions except dehydration. Also, as conjectured, stratified sampling outperforms random sampling in all but two cases.

Table 5-4: Area Under the Receiver Operating Characteristic Curve (AUROC) Results

		Random Forest		Logistic Regression	
ACS Condition	% of Sample	Random	Stratified	Random	Stratified
Any ACSC	21.1	0.69	0.71	0.70	0.72
Bacterial Pneumonia	4.3	0.63	0.66	0.71	0.71
Cellulitis	2.0	0.69	0.69	0.75	0.73
COPD	4.3	0.74	0.76	0.80	0.80
Dehydration	6.0	0.59	0.63	0.61	0.59
Diabetes	2.2	0.80	0.83	0.85	0.85
Heart Failure	4.8	0.82	0.82	0.85	0.82
UTI	3.0	0.67	0.66	0.69	0.76

5.4.2.2 Sensitivity Analysis

Like any randomized algorithm, these methods provide different results each time they are implemented. To better understand the distribution of the AUROC results, we perform a sensitivity analysis by running both the random forest and logistic regression methodologies using ten different seeds. We then report the coefficients of variation (CVs), which are included in Table 5-5 below. Since each of the CVs is well below 1.0, we conclude that the AUROC results are stable.

Table 5-5: Coefficients of Variation (CVs) Over $n = 10$ Trials

ACS Condition	Random Forest	Logistic Regression
Bacterial Pneumonia	0.031	0.018
Cellulitis	0.040	0.035
COPD	0.026	0.014
Dehydration	0.062	0.051
Diabetes	0.033	0.022
Heart Failure	0.016	0.012
UTI	0.041	0.033
Any ACSC	0.010	0.008

5.4.3 Key Findings

To interpret the supervised learning results, we must first consider that both the random forest and logistic regression methods are executed using generalized POE data. This data provides the quantity and rate of each order type, but contains no specific information regarding the orders themselves. The fact that that supervised methods achieve AUROCs averaging 0.76, and in some cases reaching as high as 0.85, despite this lack of detail is significant. The natural conclusion here is that order data strongly reflects the level of hospital care patients receive and does in fact have the potential to reveal new insights regarding avoidable admissions.

5.5 Scoring Method

Building on the conclusions of the unsupervised and supervised learning analyses, we develop a third methodology using the detailed POE data received late in the project. The concept behind this method is that specific order features can be selected and scored according to their relative association with avoidable admissions. This requires the assistance of experienced hospital physicians, but can be achieved with relatively little time and effort.

5.5.1 Methodology

One good example of this approach is the *Adult ECG Risk* feature that appears in the *Monitoring* order table. The possible values for this feature are defined in Table 5-6.

Table 5-6: Possible Values for the *Adult ECG Risk* Feature

Value	Description
Low Risk	These patients are permitted to take off their monitoring devices and use the bathroom without assistance.
Moderate Risk	These patients can remove their monitoring devices, but must be supervised on their way to and from the bathroom.
High Risk	These patients should not remove their monitoring devices for any reason.

Clearly, in this example, low-risk patients are more likely to qualify as potentially avoidable admissions, while high-risk patients are more likely to require specialized hospital resources. Accordingly, low-risk patients receive a score of one, while moderate- and high-risk patients receive scores of two and three, respectively. Once patients are scored in this manner across many features, they can be rank-ordered according to their aggregate scores. The lowest scoring patients are then investigated as avoidable admission candidates. Once validated, this process can be substituted for traditional methods to evaluate large numbers of avoidable admission patients, saving hundreds of hours in manual case review.

Consistent with the process just described, we first generate frequency distributions of the possible values for each feature from all fourteen detailed order tables. Next, we partner with physicians to identify and score features that may indicate the likelihood that an admission is avoidable. In limited cases, doctors conclude that none of the features in a table are relevant to avoidable admissions, but most often the features are determined to be binary, receiving a score of one when they indicate that an admission is avoidable and a score of two otherwise. Ultimately, this process results in fourteen scoring features derived from eleven of the detailed order tables. Table 5-7 lists these features and the POE tables they reside in, while Appendix B provides more detail regarding specifically how they are scored.

Table 5-7: Selected Scoring Features

	POE Table	Feature	Score*
1	Blood	Transfuse Product	1 or 2
2	Consult	Service	1 or 2
3	Diagnostic Procedure	Echo Priority	Other = 1, Urgent = 2
4	Diet	NPO Procedure	1 or 2
5	IV	Fluid	1 or 2
6	Lab	Test	1 or 2
7	Medication	IV Route	1 or 2
8	Medication	Med Frequency	1 or 2
9	Monitoring	Type	1 or 2
10	Monitoring	Adult ECG Risk	Low = 1, Moderate = 2, High = 3
11	Monitoring	Phys Monitoring Freq	Low = 1, Moderate = 2, High = 3
12	Radiology	Order Detail	1 or 2
13	Respiratory	Intervention	1 or 2
14	Vitals	Frequency	1 or 2

* Avoidable admissions correspond with low-scoring patients. See Appendix B for more details.

5.5.2 Results

Once these scores are applied and aggregated, the bottom ten percent of the total population is analyzed across various attributes, including age, LOS, diagnosis (at many different classification levels), discharge disposition and service, and summary payer (e.g., Medicare, Medicaid, private insurance). Due to time constraints, low-scoring patients are not validated as avoidable admissions using traditional review methods, but the results in Table 5-8 are provided to demonstrate what the next step would look like once the model is endorsed by hospital physicians.

Table 5-8: Reported Features for Bottom 10% of Scored Patients

Feature	Minimum	Median	Mean	Maximum
Score	6	53	51	64
Age	18	51	50	99
LOS (Hrs)	4	44	49	111

Feature	Details	%
Primary ICD9[1]	• Cerebral Artery Occlusion w/ Cerebral Infarction	3%
	• Syncope and Collapse	2%
	• Pneumonia, Organism Unspecified	2%
	• Acute Kidney Failure Unspecified	2%
	• Cerebral Embolism w/ Cerebral Infarction	2%
DRG[1]	• Psychoses	4%
	• Esophagitis, Gastroenteritis and Misc Digestive Disorders w/o Major Complication or Comorbidity	3%
	• Cellulitis w/o Major Complication or Comorbidity	3%
	• Intracranial Hemorrhage or Cerebral Infarction w/ Complication or Comorbidity	3%
	• Syncope Collapse	3%
	• Poisoning Toxic Effects of Drugs w/o Major Complications	3%
MDC[1]	• Diseases and Disorders of the Nervous System	16%
	• Diseases and Disorders of the Digestive System	14%
Discharge Disposition	• Home or Self Care	87%
	• Home-Health Care Service	10%
Discharge Service	• Medicine	16%
	• Neurology	15%
	• Psychiatry	6%
Summary Payer	• Medicare	25%
	• Blue Cross Blue Shield	23%
	• Medicaid Managed Care	9%

[1] ICD9s (International Classification of Diseases, Ninth Revision), DRGs (Diagnosis-Related Groups), and MDCs (Major Diagnostic Categories) are progressively higher levels of classification used by hospitals to code all diagnoses, symptoms, and procedures recorded in the hospital, primarily for insurance billing purposes.

Assuming the results in Table 5-8 are validated, they raise some interesting issues for further study. For one, the patient age range of 18 to 99 years old, with a median age of just 51, challenges the idea that there is a strong correlation between avoidable admissions and elderly patients. Further analyzing the age distribution of these individuals, as well as the correlation between age and other characteristics (such as primary diagnosis) may provide further avoidable admission insights.

The presence of some ACSCs, such as pneumonia and cellulitis, but not others, such as dehydration or UTI, is also interesting. The presence of conditions anecdotally associated with avoidable admissions, such as mental disorders ("Psychoses") and drug or alcohol abuse ("Poisoning Toxic Effects of Drugs") may provide validation for existing provider attitudes. Lastly, the presence of conditions that are normally considered severe needs to be resolved. Intracranial hemorrhage is one example, since any type of bleeding in the brain or skull is considered a medical emergency.[67] This could reflect the fact that some conditions do not require extensive care resources despite their severity, or could indicate the need to further interface with physicians to refine the model.

Chapter 6

Conclusion

This section begins by providing recommendations for future research stemming from the analyses performed in this study. It ends with a summary of the effort's accomplishments with respect to the original project goals.

6.1 Potential for Future Research

During this study, we identified several areas that would benefit from future exploration. These include:

1. **Validation & Refinement of the Scoring Methodology:** The most logical extension of this project is to work with hospital physicians to validate and refine the scoring methodology presented in Chapter 5. Validation requires physicians to manually review cases identified as avoidable to assess the level of agreement between scoring and traditional identification methods. Refinement may involve requesting new data that incorporates additional features relevant to the assessment of avoidable admissions. For

instance, one feature explored but not implemented in this study incorporates the results of specific lab tests in addition to considering the tests themselves.

2. **Methodology to Predict Hospital Capacity:** The recommendation to more systematically assess the appropriateness of transfer requests relies heavily on the ability to achieve a forward-looking view of the capacity state of the hospital. This will require the use of predictive analytics to anticipate future demand by leveraging historical trends and the expected LOS for patients entering MGH. A project focused entirely on developing this predictive model is likely appropriate.

3. **Further Exploring Unsupervised and Supervised Learning Methods:** While the unsupervised learning methods applied in this study proved inconclusive, the supervised learning methods yielded a valuable insight despite being applied to generalized order data. Applying similar methodologies to the detailed POE data could produce even clearer insights regarding avoidable admissions. Additionally, comparison of the results achieved by implementing *k*-means clustering with detailed POE data and those of the supervised learning or scoring methods developed in this study may indicate the potential (or lack of potential) associated with further unsupervised learning exploration.[68]

4. **Determining the Appropriate ROC Threshold Given the Operating Environment:** The AUROC method discussed in Chapter 4 was helpful in evaluating the quality of the random forest and logistic regression classifiers. However, one issue not addressed is the fact that, in an operational environment, one must choose an appropriate threshold at

which to operate. In other words, the hospital must decide at what point along the ROC curve it is acceptable to operate given both the costs and benefits associated with correctly identifying an avoidable admission or incorrectly declaring one that is not. Considering that human lives are involved, it is safe to say the threshold would be high, but an analysis to determine the precise value is necessary before applying the methodologies discussed.

6.2 Conclusions

This project set out to understand precisely what is driving the volume growth of ED visits and inpatient admissions through the ED at MGH, as well as to explore if any of those visits or admissions could be avoided while preserving patient safety and quality of care. By developing a methodology to quantify avoidable admission candidates among patients transferring to MGH from other facilities, we discovered that transfers alone are likely responsible for at least some of the capacity-related symptoms MGH experienced in 2015. This prompted a robust set of recommendations aimed at improving the way MGH manages transfer requests.

Supervised and unsupervised learning methods were then used to confirm that patient order data can, in fact, provide useful insights regarding avoidable admissions. That conclusion then fed the development of an automated methodology to identify avoidable admission candidates without requiring manual case review by physicians. Although the results of this methodology could not be verified within the time constraints of this study, the work provides a solid basis for future avoidable admissions research.

Appendix A:

Ambulatory Care-Sensitive Conditions (ACSCs)

ACSC	ICD9 Codes
Bacterial Pneumonia	481, 485, 486, 482.2, 482.9, 483.0, 483.1, 483.8, 482.30 – 482.32, 482.39, 482.41, 482.42
Cellulitis	681.00 – 681.02, 681.10, 681.11, 681.9, 682.0 – 682.9
Chronic Obstructive Pulmonary Disorder (COPD)	490, 494, 496, 466.0, 491.0, 491.1, 491.8, 491.9, 492.0, 492.8, 494.0, 494.1, 491.20 – 491.22, 493.00 – 493.02, 493.10 – 493.12, 493.20 – 493.22, 493.81, 493.82, 493.90 – 493.92
Dehydration	861 – 864, 276.0, 276.5, 276.50 – 276.52
Diabetes	250.10 – 250.13, 250.20 – 250.23, 250.30 – 250.33, 250.02, 250.03, 250.40 – 250.43, 250.50 – 250.53, 250.60 – 250.63, 250.70 – 250.73, 250.80 – 250.83, 250.90 – 250.93
Heart Failure	402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, 428.0, 428.1, 428.20, 428.30, 428.9, 398.91, 428.21 – 428.23, 428.31 – 428.33, 428.40 – 428.43
Urinary Tract Infection (UTI)	590.2, 590.3, 590.9, 595.0, 595.9, 599.0, 590.10, 590.11, 590.80, 590.81

This page intentionally left blank

Appendix B:

Details of Scoring Methodology

1	Table:	Blood
	Feature:	Transfuse Product

Score = 1	Score = 2
• Immune Globulin IV • Prothrombin Complex Concentrate: (4-Factor) • Factor IX (Recombinate) • Factor VIII (Recombinate) • Cryoprecipitate IV • Immune Globulin IM • Pheresis	• RBC • Platelet Concentrate • 25% Albumin (1 Bottle = 50 ml) • 5% Albumin (1 Bottle = 250 ml)

2	Table:	Consult
	Feature:	Service[1]

Score = 1		Score = 2
• Physical Therapy • Nutrition • Social Service • Occupational Therapy • PT (Physical Therapy) • Chaplaincy • Speech Language Pathology • Anticoagulation Management Services (AMS) Clinic • Speech/Swallowing • Psychiatry • IV Team - PICC • OT • Palliative Care	• Smoking Cessation Program • NULL • Pressure Ulcers / Wound • Pressure Ulcers • Brace Shop • Pain Service - Chronic/Cancer Pain • Case Management • Addictions • Pain Service - Acute • Respiratory PEPP-DOSE/COPD Teaching • Respiratory Therapy • GI	• RBC • Platelet Concentrate • 25% Albumin (1 Bottle = 50 ml) • 5% Albumin (1 Bottle = 250 ml)

[1] Due to the number of consult services scored as 1, only the 25 most common are reported here.

3	Table:	Diagnostic Procedure
	Feature:	Echo Priority

Score = 1	Score = 2
• Routine • Null	• Urgent

4	Table:	Diet
	Feature:	NPO Procedure[2]

Score = 1		Score = 2
• EGD • RUQUS • Colonoscopy • Stress Test • Colonoscopy • Possible Cath • Renal Ultrasound • Stress • Stress Test • Possible EGD • LHC • Endoscopy • OR	• EGD • Possible ERCP • DCCV • GIFTS ORTHO Surgery • RUQ US • Bronch • IR • ERCP • Flex Sig • IR Drain • Paracentesis • Possible Stress Test	• ERCP • Cath • IR Drainage • Cardiac Cath • Cardioversion • MRCP • Bronchoscopy • TEE

[2] Due to the number of NPO procedures scored as 1, only the 25 most common are reported here.

5	Table:	IV
	Feature:	Fluid[3]

Score = 1		Score = 2
• NS • D5 1/2NS • D5 NS • Lactated Ringers • D5W • D5 LR • 1/2 NS • LR • D10W • D10 1/2NS • D10 NS • D5 1/4NS • D5NS • D5W with 150mEq of NaHCO3	• D5W with 3 amps Sodium Bicarb • D5W with 3 amps of Bicarb in Each Liter • Lactated Ringer's • Sterile Water • 1/2 NS + 20 mEq K • 150meQ NaHCO3 Mixed in 1L D5W • 3% Sodium Chloride • D10NS • D2.5 1/2NS • D5 1/2 NS + 40meq K • D5LR • Physical	• 3% NaCl • 3% Saline solution • 3% Saline

[3] Due to the number of IV fluids scored as 1, only the 25 most common are reported here.

6	Table:	Lab
	Feature:	Test[4]

Score = 1		Score = 2
• Electrolytes • Glucose • BUN/Creatinine • CBC with Diff • Magnesium • Phosphorus • Calcium • CBC • PT-INR • LFTs (Hepatic Panel) • Basic Metabolic Panel 7 • Ca/Mg/PO4 • PTT • ED Kiosk (Urinalysis)	• Urine Culture/Sensitivity • Blood Culture/Sensitivity • ED Kiosk (Cardiac Markers) • U/A (Urinalysis) • NT-proBNP • Hemoglobin A1c • Drugs of Abuse (Urine) • TSH • Sed Rate (ESR) • C- Reactive Protein • Vancomycin (Trough)	• Lactic Acid (Lactate) • Troponin T • Lipase • Venous Blood Gas • C.Difficile Toxin Assay • Ammonia • Arterial Blood Gas

[4] Due to the number of lab tests scored as 1, only the 25 most common are reported here.

7	Table:	Medication
	Feature:	IV Route[5]

Score = 1		Score = 2
• PO	• Right Eye	• IV
• SC	• Left Eye	• IV Continuous Infusion
• IM	• Swish & Swallow	• IV Push
• NEB	• PCA	• IV Bolus
• INH	• Mouthwash	
• Transdermal	• J Tube	
• TOP	• OU	
• PR	• Swish & Spit	
• SL	• PV	
• NAS	• ID	
• Both Eyes	• OS	
• G Tube	• OD	
• PNGT		

[5] Due to the number of IV routes scored as 1, only the 25 most common are reported here.

8	Table:	Medication
	Feature:	Med Frequency[6]

Score = 1		Score = 2
• QD	• BID BEFORE BREAKFAST AND BEFORE SUPPER	• Q6H
• BID	• QAM BEFORE BREAKFAST	• Q4H
• x1	• QWEEK	• Q8H
• TID	• AS DIRECTED	• Q2H
• QHS	• Q72H	• Q1H
• QPM	• qhs	• Q5MINUTES
• Q12H	• QPM BEFORE SUPPER	• Q3H
• NULL	• bid	• Q30MINUTES
• QAM	• 1x	• q6h
• Q24H	• qd	• q8h
• QID	• tid	• q4h
• AC		• q2h
• AC+HS		• Q10MINUTES
• QOD		• Q6h
		• q3h

[6] Due to the number of medication frequencies scored as 1, only the 25 most common are reported here. Similarly, only the 15 most common frequencies scored as 2 are reported. Any medication administered on a recurring basis at an interval of eight hours or less is scored as 2.

9	**Table:**	Monitoring
	Feature:	Type

Score = 1	**Score = 2**
• ECG Monitoring • Pulse Oximetry Monitoring • Neuro Checks • O2 Saturation Monitoring • Pain Assessment • OB Monitoring – Non-Stress Test • Pulse Volume Recording	• Cardiac Monitoring • Hemodynamics Per ICU Routine • OB Monitoring - Electronic Fetal Monitoring

10	**Table:**	Monitoring
	Feature:	Adult ECG Risk

Score = 1	**Score = 2**	**Score = 3**
• Low Risk	• Moderate Risk	• High Risk

11	**Table:**	Monitoring
	Feature:	Monitoring Frequency

Score = 1	**Score = 2**	**Score = 3**
• Null • Other • Per ED Care Unit Routine • Twice Weekly • Q8h	• Q4h	• ICU Routine • Q1h • Q2h

12	Table:	Radiology
	Feature:	Order Detail[7]

Score = 1		Score = 2
• Plain: Portable Chest • Plain: Chest PA & Lateral • CT: Abdomen/Pelvis • CT: Head • MRI: Head • CT: Chest • U/S: RUQ • MRI: Neck • U/S: Renal • CT: Chest (PE Protocol) • Plain: Portable KUB • Plain: KUB & Upright • U/S: Abdominal	• Nucl Card: Adenosine/A2A Agonist Stress • CT: CTA Head/Neck • Plain: Pelvis & Hips • CT: Cervical Spine • Nucl Card: Standard Bruce (Imaging) • CT: Neck • MRI: Abdomen • CT: CTA Head • Plain: Pelvis • CT: Cardiac • MRI: Lumbosacral spine • MRI: Cervical spine	• MRI: Entire spine • MRI: MRCP • NM: HIDA

[7] Due to the number of radiology orders scored as 1, only the 25 most common are reported here.

13	Table:	Respiratory
	Feature:	Intervention

Score = 1	Score = 2
• O2 and Aerosol Therapy • NPPV/BiPAP/CPAP • Special Procedures • Teaching Procedures	• Intubation / Mechanical Ventilation • Artificial Airway Management

14	**Table:**	Vitals
	Feature:	Frequency

Score = 1	**Score = 2**
• Routine • Q shift • NULL • Other • Daily • Q8h • On Admission • Per ED Care Unit Routine • QOD • Strict • Post Procedure Routine • Weekly	• Q4h • Q1h • Q2h • ICU Routine

This page intentionally left blank

Bibliography

[1] Massachusetts General Hospital (MGH). *Massachusetts General Hospital - Hospital Overview*, accessed January 5, 2017. http://www.massgeneral.org/about/overview.aspx.

[2] Massachusetts General Hospital (MGH). *Massachusetts General Hospital - #1 in the Nation*, accessed January 5, 2017. http://www.massgeneral.org/News/newsarticle.aspx?id=5409.

[3] Massachusetts General Hospital *(MGH). Massachusetts General Hospital Receives Highest Nursing Credential with Prestigious Magnet Recognition ... Again*, accessed January 8, 2017. http://www.massgeneral.org/about/pressrelease.aspx?id=1587.

[4] Massachusetts General Hospital (MGH). *Mass General Milestones*, accessed January 5, 2017. http://www.massgeneral.org/news/milestones/.

[5] Harvard Medical School Center for Evaluation. *Guide to the Clerkships*. Harvard Medical School, Boston, 31st Edition, accessed January 1, 2017.

[6] Massachusetts General Hospital (MGH). *Massachusetts General Hospital – Partners Healthcare*, accessed January 1, 2017. http://www.massgeneral.org/partners.aspx.

[7] Jonas Hiltrop. Modeling Neuroscience Patient Flow and Inpatient Bed Management. Master's thesis, Massachusetts Institute of Technology (MIT), 2014.

[8] Ashleigh Royalty Range. Improving Surgical Patient Flow Through Simulation of Scheduling Heuristics. Master's thesis, Massachusetts Institute of Technology (MIT), 2013.

[9] Noa Ben-Zvi. Operations Research Applied to Operating Room Supply Chain. Master's thesis, Massachusetts Institute of Technology (MIT), 2014.

[10] Sara A. Dolcetti. Analyzing the Impact of Delays for Patient Transfers from the ICU to General Care Units. Master's thesis, Massachusetts Institute of Technology (MIT), 2015.

[11] Trevor A. Schwartz. Improving Surgical Patient Flow in a Congested Recovery Area. Master's thesis, Massachusetts Institute of Technology (MIT), 2012.

[12] Matthew R. Schlanser. Optimization of Surgical Supply Inventory and Kitting. Master's thesis, Massachusetts Institute of Technology (MIT), 2013.

[13] Wendi Rieb. Increasing Patient Throughput in the MGH Cancer Center Infusion Unit. Master's thesis, Massachusetts Institute of Technology (MIT), 2015.

[14] Adam Marshall. Improving Outpatient Non-Oncology Infusion through Centralization and Scheduling Heuristics. Master's thesis, Massachusetts Institute of Technology (MIT), 2016.

[15] Sean McNichols. Reducing Intraday Patient Wait Times Through Just-In-Time Bed Assignment. Master's thesis, Massachusetts Institute of Technology (MIT), 2015.

[16] Massachusetts General Hospital (MGH). *The Summer M. Redstone Emergency Department*, accessed January 7, 2017. https://giving.massgeneral.org/the-sumner-m-redstone-emergency-department/.

[17] Massachusetts General Hospital (MGH). *Emergency Medicine – About Us*, accessed January 5, 2017. http://www.massgeneral.org/emergencymedicine/about/.

[18] American Trauma Society. *Trauma Center Levels Explained*, accessed March 29, 2017. http://www.amtrauma.org/?page=traumalevels.

[19] Massachusetts General Hospital (MGH). *Emergency Department Renovates and Expands to Lunder Building*, accessed January 7, 2017. http://www.massgeneral.org/news/newsarticle.aspx?id=2705.

[20] Andrew Johnston. Quantifying the Impact of Care Team Discontinuities on Medically Unnecessary Delays in Inpatient Flow. Master's thesis, Massachusetts Institute of Technology (MIT), 2016.

[21] Grabowski, Beth G. "Re: Bed Request Time Intervals." Message to Jordan Hoffmann, January 31, 2017. E-mail.

[22] Slavin, Peter L. "From the Desktop of Peter L. Slavin, MD." Message to "All User MGH" distribution list, February 29, 2016. E-mail.

[23] Allwes, Deborah. Update – Reducing Emergency Department Patient Boarding [Memorandum]. Boston, MA: Executive Office of Health and Human Services. June 3, 2015.

[24] Morris, Edward B. "RE: Data Request - General Medicine Patient Volume & LOS." Message to Kimia Ghobadi, May 3, 2017. E-mail.

[25] Boston Globe. *MGH Continues to Grapple with Patient Overcrowding*, accessed January 10, 2017. https://www.bostonglobe.com/business/2016/03/01/mgh-continues-grapple-with-patient-overcrowding/FUl4h1kIrlawLfSvroiIxO/story.html.

[26] Weinberger et al. "Does Increased Access to Primary Care Reduce Hospital Admission? Veterans Affairs Cooperative Study Group on Primary Care and Hospital Readmission." en In: *The New England Journal of Medicine* (1996), 334, 22, 1441, 1447, 10.1056/NEJM199605303 342206,8618584.

[27] Freund et al. "Strategies for Reducing Potentially Avoidable Hospitalizations for Ambulatory Care-Sensitive Conditions." en In: *Annals of Family Medicine* (2013), 363-370, DOI: 10.1370/afm.1498.

[28] Muenchberger et al. "Determinants of Avoidable Hospitalization in Chronic Disease: Development of a Predictor Matrix." en In: *Centre for National Research on Disability and Rehabilitation, Griffith Institute of Health and Medical Research* (2008). http://www.gpqld.com.au/content/Document/3%20Programs/Collaborative%20Research%20Hub/Hospital%20Avoidance%20Review%20Paper_FINAL.pdf.

[29] Sanmartin et al. "Hospitalizations for Ambulatory Care Sensitive Conditions (ACSC): The Factors that Matter." en In: *Longitudinal Health and Administrative Data Research Team, Health Research Working Paper Series* (2011).

[30] Moy et al. "Potentially Preventable Hospitalizations — United States, 2001–2009." en In: *Morbidity and Mortality Weekly Report* (November, 2013), Vol. 62, No. 3.

[31] Thorpe et al. "Rural-Urban Differences in Preventable Hospitalizations Among Community-Dwelling Veterans With Dementia." en In: *The Journal of Rural Health* (2010), 146–155, DOI: 10.1111/j.1748-0361.2010.00276.x.

[32] Nayar et al. "Preventable Hospitalizations: Does Rurality or Non-Physician Clinician Supply Matter?" en In: *Journal of Community Health* (2012), 37:487–494, DOI 10.1007/s10900-011-9468-1.

[33] Beijer et al. "Hospitalisations Caused by Adverse Drug Reactions (ADR): A Meta-Analysis of Observational Studies." en In: *Pharmacy World and Science* (2002), 24(2): 46-54.

[34] Fingar et al. "Trends in Potentially Preventable Inpatient Hospital Admissions and Emergency Department Visits." en In: *Healthcare Cost and Utilization Project (HCUP) Statistical Brief #195* (November 2015). http://www.hcup-us.ahrq.gov/reports/statbriefs/sb195-Potentially-Preventable-Hospitalizations.pdf.

[35] Grabowski, Beth G. "Review of ED Patient Demographics and Transfers from Outside Facilities." February 17, 2016, PowerPoint file.

[36] Central Massachusetts Emergency Medical Systems Corporation (CMEMSC). *Central Medical Emergency Direction (CMED)*, accessed January 8, 2017. http://www.cmemsc.org/index.php/cmed.

[37] Emergency Nurses Association. *Position Statement - Observation Units/Clinical Decision Units*, accessed January 8, 2017. https://www.ena.org/SiteCollectionDocuments/Position%20Statements/Archived/ObservationUnits.pdf

[38] Healthcare Design Magazine. *Fast-Track Treatment in the Emergency Room*, accessed January 8, 2017. http://www.healthcaredesignmagazine.com/architecture/fast-track-treatment-emergency-room/.

[39] Massachusetts General Hospital(MGH). *Pediatric Emergency Medicine – Overview*, accessed January 7, 2017. http://www.massgeneral.org/children/services/treatmentprograms.aspx?id=1603.

[40] Massachusetts General Hospital(MGH). *MGH Psychiatry - Acute Psychiatry Service*, accessed January 8, 2017. http://www.massgeneral.org/psychiatry/services/aps_home.aspx.

[41] Climber. *Job Detail for Director, National Network Development and Integration*, accessed May 1, 2017. http://jobs.climber.com/jobs/industry/Boston-MA-00613-USA/Director-National-Network-Development-and-Integration/82781795.

[42] Massachusetts General Hospital. *Mission*, accessed May 26, 2017. http://www.massgeneral.org/about/overview.aspx.

[43] Boston Globe. *Steward, Partners Hospitals Reach Deal on Trauma Care*, accessed March 26, 2017. https://www.bostonglobe.com/business/2012/10/18/steward-strikes-trauma-care-alliance-with-partners-strengthening-ties-between-two-largest-health-care-providers-massachusetts/ZpxXZkyDKD2PEUhygYsTUM/story.html.

[44] American College of Emergency Physicians. *EMTALA*, accessed March 3, 2017. https://www.acep.org/news-media-top-banner/emtala/.

[45] Shriners Hospital for Children. *Welcome to Shriners Hospital for Children*, accessed March 23, 2017. https://www.shrinershospitalsforchildren.org/.

[46] EMTALA.com. *Frequently Asked Questions about the Emergency Medical Treatment and Active Labor Act (EMTALA)*, accessed March 3, 2017. http://www.emtala.com/faq.html.

[47] Cornell University Law School Legal Information Institute. *42 U.S. Code § 1395dd - Examination and Treatment for Emergency Medical Conditions and Women in Labor*, accessed March 24, 2017. https://www.law.cornell.edu/uscode/text/42/1395dd.

[48] U.S. National Library of Medicine. *MedLine Plus: Abdominal Aortic Aneurysm*, accessed March 20, 2017. https://medlineplus.gov/ency/article/000162.htm.

[49] U.S. National Library of Medicine. *MedLine Plus: Subarachnoid Hemorrhage*, accessed March 20, 2017. https://medlineplus.gov/ency/article/000701.htm.

[50] ECG Medical Training. *What is STEMI?*, accessed March 20, 2017. https://www.ecgmedicaltraining.com/what-is-a-stemi/.

[51] Allscripts. *Allscripts EPSi*, accessed February 25, 2017. http://ca.allscripts.com/products-services/products/epsi.

[52] Massachusetts General Hospital. *MGH TeleHealth – Meet the Team*, accessed April 10, 2017. http://www.mghtelehealth.org/about-us/meet-the-team/.

[53] Centers for Medicare and Medicaid Services. *Defining the Medicare Severity Diagnosis Related Groups (MS-DRGs)*, accessed February 28, 2017. https://www.cms.gov/ICD10 Manual/version34-fullcode-cms/fullcode_cms/Defining_the_Medicare_Severity_ Diagnosis_Related_Groups_(MS-DRGs)_PBL-038.pdf.

[54] Harvard Business Review. *Operations Management: Six Myths of Product Development*, accessed April 29, 2017. https://hbr.org/2012/05/six-myths-of-product-development.

[55] Wikipedia. *Computerized Physician Order Entry*, accessed May 10, 2017. https://en.wiki pedia.org/wiki/Computerized_physician_order_entry.

[56] Agency for Healthcare Research and Quality. *Inpatient Computerized Provider Order Entry (CPOE)*, accessed May 12, 2017. https://healthit.ahrq.gov/ahrq-funded-projects/emerging-lessons/computerized-provider-order-entry-inpatient/inpatient-computerized-provider-order-entry-cpoe.

[57] MathWorks. *Unsupervised Learning*, accessed May 31, 2017. https://www.mathworks.com/ discovery/unsupervised-learning.html.

[58] MedCalc. *Logistic Regression*, accessed May 31, 2017. https://www.google.com/search?q= logistic+regression&oq=logistic+regression&aqs=chrome..69i57j0l5.2447j0j7&sourceid=chrom e&ie=UTF-8.

[59] Manski et al. "Potentially Preventable Hospitalizations: Are They a Useful Marker of Access to and Experience of Care in General Practice Among People with Type 2 Diabetes?" en. In: *Australian Journal of Primary Health* (2015) 21(2): 214-220.

[60] Ben-Assuli et. al. "The Impact of EHR and HIE on Reducing Avoidable Admissions: Controlling Main Differential Diagnoses." en. In: *BNC Medical Informatics and Decision Making* (April 2013) 13:49.

[61] Brownell et. al. "Trends in Emergency Department Visits for Ambulatory Care Sensitive Conditions by Elderly Nursing Home Residents, 2001–2010." en. In: *JAMA Internal Medicine* (January 2014) 174(1): 156–158. DOI: 10.1001/jamainternmed.2013.11821.

[62] Laditka et. al. "Insurance Status and Access to Primary Health Care: Disparate Outcomes for Potentially Preventable Hospitalization." en. In: *Journal of Health & Social Policy* (2004) Vol. 19(2). DOI: 10.1300/J045v19n02_04.

[63] Saha et. al. "Are Preventable Hospitalizations Sensitive to Changes in Access to Primary Care? The Case of the Oregon Health Plan." en. In: *Medical Care* (August 2007) Vol. 45, Num. 8. ISSN: 0025-7079/07/4508-0712.

[64] Ward. "Avoidable Hospitalizations in Patients with Systemic Lupus Erythematosus." en. In: *Arthritis & Rheumatism* (February 2008) Vol. 59, No. 2, pp 162–168. DOI 10.1002/art.23346.

[65] Ouslander et al. "Potentially Avoidable Hospitalizations of Nursing Home Residents: Frequency, Causes, and Costs." en. In: *Journal of the American Geriatric Society* (April 2010) 58:627–635.

[66] Ticona et al. "Ambulatory Care Sensitive Conditions and Potential Opportunities." May 18, 2016, PowerPoint file.

[67] Cleveland Clinic. *Intracranial Hemorrhage, Cerebral Hemorrhage and Hemorrhagic Stroke*, accessed May 5, 2017. https://my.clevelandclinic.org/health/articles/intracranial-hemorrhage.

[68] Finch, Holmes. "Comparison of Distance Measures in Cluster Analysis with Dichotomous Data." en In: *Journal of Data Science* (2005), 85-100.

[69] JMP. *K-Means Clustering*, accessed May 31, 2017. http://www.jmp.com/support/help/K-Means_Clustering.shtml.

[70] Berkeley Department of Statistics. *Random Forests*, accessed May 31, 2017. https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm#intro.

[71] Wikipedia. *Receiver Operating Characteristic*, accessed May 31, 2017. https://en.wikipedia.org/wiki/Receiver_operating_characteristic.